Agri-Guard: IoT-Based Network for Agricultural Health Monitoring with Fault Detection

Kushagra Singh, Kafil Abbas Momin, M. Nishal, Chinmay Sultania and Madhav Rao
Dept. of Electronics and Communication Engineering,
International Institute of Information Technology Bangalore, Karnataka, India

Keywords: Precision Agriculture, Gas Sensors, ESP8266, IoT Devices, Thermal Imaging, Sustainable Farming, Crop Productivity.

Abstract: Agricultural sector is increasingly adopting advanced technologies to enhance crop productivity and sustainability. Precision agriculture leverages IoT devices, sensors, and data analytics to monitor and manage various environmental parameters, addressing challenges such as global food demand, climate change, and resource optimization. Previous research has demonstrated the efficacy of wireless sensor networks (WSNs) and remote sensing technologies in improving irrigation efficiency and early disease detection. However, these systems often assume that all components continue to operate, thereby offering an incomplete view. This study presents an advanced agricultural monitoring system referred to as Agri-Guard that integrates a wide array of sensors to measure temperature, humidity, soil moisture, and gases like CO_2, methane and ammonia. By utilizing an ESP8266 microcontroller and IoT connectivity, the system ensures seamless data transmission and real-time processing. Additionally, a centralized hub, equipped with a Raspberry Pi 5 and a thermal camera, enhances the detection of crop anomalies, and an inoperative sensor hub. The sensor hub in the form of a cone is optimally designed to detect environmental parameters besides being rainproof. The proposed Agri-Gaurd setup clearly demonstrated the lack of manure and water from the sensors' data, whereas thermal imaging showcased the classification of 92.7% between a dead and alive plant. The anomaly between an operating and non-operating Agri-cone was found to be in complete agreement (100%). The proposed system represents a significant improvement over existing solutions, empowering farmers with precise data and faulty hub detection, leading to quick recovery and more sustainable farming practices.

1 INTRODUCTION

The agricultural sector has undergone a significant transformation in recent years, driven by the advent of precision agriculture and the integration of advanced technologies (Condran et al., 2022), (Patil et al., 2023), (Liakos et al., 2018), (Taghizadeh-Mehrjardi et al., 2020), (Sharma et al., 2021). Precision agriculture involves the use of IoT devices, sensors, and data analytics to monitor and manage critical agricultural parameters, aiming to optimize crop yields and resource use while minimizing environmental impact (Vitali et al., 2021), (Villa-Henriksen et al., 2020), (Talavera et al., 2017), (Farooq et al., 2019), (Naseer et al., 2024), (AlZubi and Galyna, 2023). This technological evolution has been crucial in addressing the challenges posed by increasing global food demand, climate change, and the need for sustainable farming practices (Wu et al., 2010), (Roux et al., 2018), (Nóbrega et al., 2019), (Bruinsma, 2009). Previous research has highlighted the potential of IoT-based solutions in enhancing agricultural productivity. Wireless sensor networks (WSNs) have been extensively utilized to monitor soil moisture and temperature, providing real-time data that

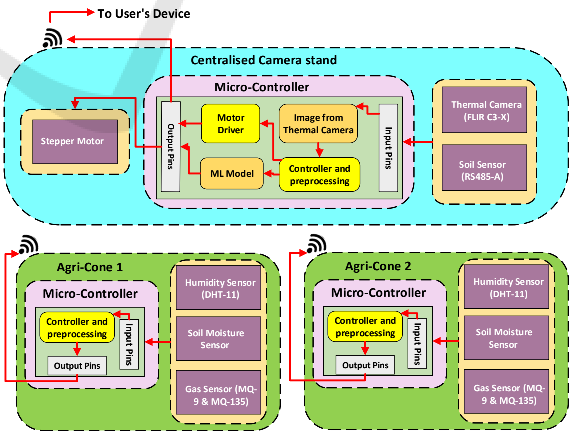

Figure 1: Schematic showing the overview of Agri-Guard and flow of data.

Singh, K., Momin, K. A., Nishal, M., Sultania, C. and Rao, M.
Agri-Guard: IoT-Based Network for Agricultural Health Monitoring with Fault Detection.
DOI: 10.5220/0013209500003944

In *Proceedings of the 10th International Conference on Internet of Things, Big Data and Security (IoTBDS 2025)*, pages 223-230
ISBN: 978-989-758-750-4; ISSN: 2184-4976

helps farmers optimize irrigation schedules, thereby conserving water and improving crop health (Patil et al., 2023), (Marwa et al., 2020). Additionally, remote sensing technologies, including thermal imaging and multispectral cameras, have been employed to detect early signs of crop diseases and stress (Pallagani et al., 2019), (Barjaktarovic et al., 2024), (Wilson et al., 2023), (Cui et al., 2021), (Hassan et al., 2021), (Fevgas et al., 2023), (Toscano et al., 2024), (Zhu et al., 2023). These technologies allow for timely interventions, reducing crop loss, maintaining soil moisture, and improving overall yield (Bai et al., 2019). However, these systems often operate in isolation, focusing on specific parameters without providing a holistic view of the agricultural environment. Several related works have attempted to bridge this gap by integrating multiple sensors and data sources into a unified monitoring system. For example, systems combining soil sensors with weather stations have been developed to offer comprehensive environmental monitoring, aiding in more accurate decision-making (Marwa et al., 2020), (Hashmi et al., 2024), (Shaikh et al., 2022a), (Ahmed et al., 2024), (Lin et al., 2023), (Ibraiwish et al., 2024), (Caruso et al., 2021a), (Jani and Chaubey, 2022). Another notable advancement is the use of drone technology equipped with various sensors to survey large agricultural fields, providing high-resolution data on crop conditions and facilitating precision farming (Caruso et al., 2021b), (Panjaitan et al., 2022), (Mohyuddin et al., 2024), (Shaikh et al., 2022b), (Reddy Maddikunta et al., 2021), (Mukhamediev et al., 2023), (Verma et al., 2020), (Jasim et al., 2023). Despite these advancements, most of these works do not cater to the on-field problems where few of the sensors are at fault leading to an incomprehensive view. Hence besides on-field sensory information, the operative status of installed components is equally important.

The current work seeks to build upon these foundations by developing a more sophisticated and comprehensive agricultural monitoring system. In addition to the array of sensors that measure temperature, humidity, soil moisture, and gases such as CO_2, methane, and ammonia, this system also offers a mechanism to detect whether the sensor hubs are manipulated from the housed setup. In general, the proposed two-level Physical-security-enabled sensing provides a holistic view of the agricultural environment. Advanced microcontrollers and IoT connectivity ensure that data from these sensors is seamlessly transmitted and processed, offering real-time insights and alerts to farmers. The incorporation of thermal imaging enhances the system's capability to not only detect crop anomalies such as pest infestations and diseases at an early stage but also alert any faulty sensory hubs installed. This work improves upon previous systems by offering a fully integrated solution that not only monitors a wide range of environmental parameters but also processes and analyzes the data to provide meaningful insights. The use of a centralized data processing hub allows for the aggregation and analysis of data from multiple sensors, ensuring that farmers receive comprehensive and actionable information. Furthermore, the automation of data collection and analysis reduces the need for manual intervention, allowing farmers to focus on other critical tasks. The proposed system enables more precise and timely interventions, ultimately leading to improved crop yields and more sustainable farming practices.

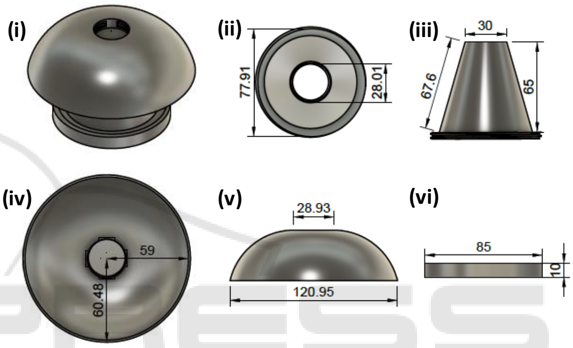

Figure 2: 3-D CAD files showing the, (i) overall structure of the Agri-cone, (ii),(iii) the structure of the conical body and (iv),(v),(vi) the hemispherical top.

2 PROPOSED AGRI-GUARD DESIGN

Agri-Guard consists of two sets of devices: The IoT-based Agri-cones and a Centralized Camera stand as shown in Figure 1. The Agri-cones consist of an array of sensors including temperature, humidity, moisture, CO_2 and methane gas sensors. These host of sensors provide crucial details about the plant health. These sensors are interfaced using an ESP8266 microcontroller, which is Wi-Fi and Bluetooth enabled to transfer these vital data to the hub of the IoT network placed under the Centralized Camera stand. The Centralized Camera stand receives data from all the Agri-cones placed around it in its vicinity and relays the data to the control unit, i.e. the user's device. The Centralized Camera stand is a height-adjustable metal stand mounted with a thermal camera. This thermal camera is allowed to rotate through two degrees of freedom (DOF), allowing it a 360° view of its surroundings. The base of the stand consists of an 8-in-1

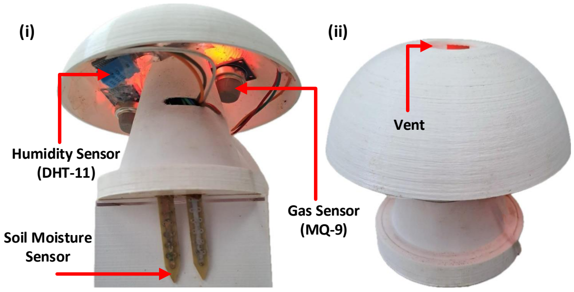

Figure 3: The Agri-cone, (i) Bottom view and (ii) Front view.

soil parameter sensor which enables it to monitor the soil conductivity, pH, and levels of nitrogen, phosphorous and sodium (NPK) among others. The base also consists of an IoT network hub that relays data from all the Agri-cones in its vicinity to the base station for efficient monitoring. The thermal camera on top of the stand serves two key purposes. First, it monitors the health of the plants within its vicinity, detecting whether any plants are showing signs of stress, have died, or are under threat from parasitic attacks. This allows the system to issue timely warnings, enabling users to take preventive or corrective actions to maintain plant health.

In addition, the activity of the sensors within each Agri-cone is continuously monitored to predict any anomalies or malfunctions. If sensor data indicates an issue, the thermal camera is used to confirm the problem by visually checking the operational status of the Agri-cone. This combination ensures that both plant health and device functionality are accurately monitored, providing a more reliable and comprehensive system for agricultural management.

2.1 Agri-Cones

The Agri-cone features a conical body topped with a hemispherical cover (Figure 2), combining aesthetic design with functional utility. The cone-shaped body ensures stable and secure placement in the soil, with a wide base that helps anchor it firmly even in varying soil conditions. The hemispherical top cover serves as a critical element, providing dual functionalities: protection and gas distribution. This cover shields the internal components from rain, dust, and other environmental elements, thereby enhancing the durability and longevity of the device. Additionally, its design allows gases emanating from the soil to spread evenly to the gas sensors mounted beneath it and escape from the vent present at the top, ensuring accurate gas readings and continuous flow of gases (Figure 3). The entire structure of the Agri-cone is fabricated from PLA Generic White material and 3D printed using the Ultimaker 3 Extended, ensuring precision and consistency in the build. To further protect the device, the entire structure is sealed and coated with a water-repellent layer. This coating prevents moisture ingress, safeguarding the internal electronics from potential damage caused by water seepage. At the heart of the Agri-cone is the ESP8266 microcontroller, equipped with both Wi-Fi and Bluetooth capabilities, allowing for seamless data transfer to the IoT network hub located at the base of the Centralized Camera Stand. Inside the cone, the microcontroller is accompanied by a battery and sensors for measuring soil moisture and temperature. These sensors are housed within the conical body, providing crucial data on the soil's physical conditions. The moisture sensor detects the water content in the soil, which is vital for maintaining optimal plant hydration levels. The temperature sensor monitors the soil temperature, ensuring that it remains within a suitable range for plant growth. Under the hood of the top cover, the gas sensors and humidity sensors are strategically placed. The gas sensors are designed to detect key gases such as carbon dioxide (CO_2), methane, and ammonia, which are indicative of soil respiration, microbial activity, and nutrient cycles. Monitoring these gases provides insights into the biological and chemical processes occurring within the soil. Ammonia levels, in particular, can indicate the presence of nitrogen-fixing bacteria and the decomposition of organic matter. The DHT-11 humidity sensors, on the other hand, measure the air moisture levels around the plants, which is crucial for preventing diseases and ensuring healthy plant growth.

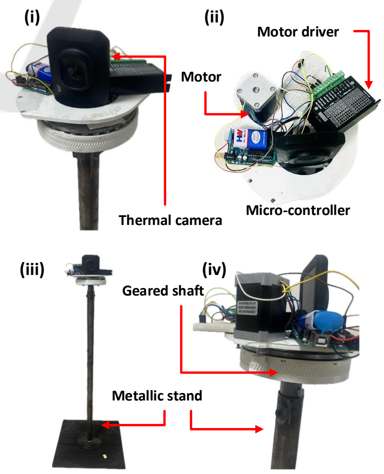

Figure 4: Structure of the Centralised Camera stand along with the various components mounted on it.

2.2 Centralised Camera Stand

The Centralised Camera Stand, an essential part of the Agri-Guard system, is designed to integrate and process data from multiple sources for comprehensive field monitoring. It features a height-adjustable metallic stand, ensuring stability and durability in various environmental conditions. At its base, a Raspberry Pi 5 acts as the central hub, receiving data from all neighbouring Agri-cones via the IoT network. The Raspberry Pi processes this data, flagging any irregularities and transforming it into meaningful information for the user. Mounted atop the stand is a PLA Generic White structure housing the FLIR C3-X Compact thermal camera. This camera, capable of detecting thermal anomalies such as pest infestations and crop diseases, interfaces with the Raspberry Pi to send thermal images to the user's device for detailed analysis (Figure 5). To achieve a comprehensive 360° field view, the thermal camera is mounted on a motorized platform that allows it to rotate freely along two degrees of freedom (DOF) as shown in Figure 4. Programmed to survey the field every six hours, the camera captures 12 images per rotation, each covering a 30-degree segment, ensuring thorough monitoring. Embedded in the base of the stand is a 7-in-1 RS485 JXCT soil sensor, providing critical parameters such as pH, electrical conductivity (EC), and NPK levels. These parameters are vital for long-term soil health monitoring. The integration of these advanced technologies in the Centralized Camera Stand enables efficient data management and provides farmers with actionable insights, enhancing productivity and sustainability in agricultural practices.

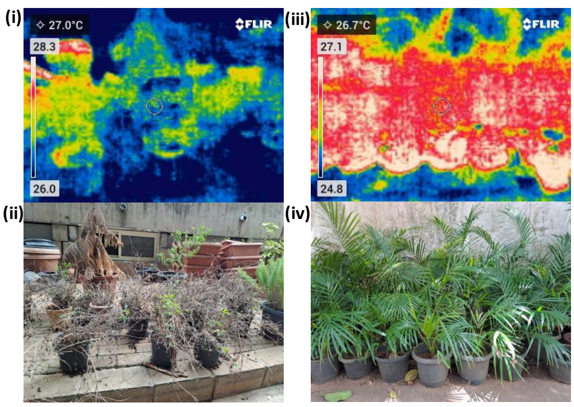

Figure 5: Images obtained by the FLIR C3-X Thermal Camera mounted on the Stand along with their original color image.

2.3 Advantages of Wi-Fi Communication

In this experimental setup, Wi-Fi was chosen as the primary communication protocol for several reasons:

Higher Data Throughput: Wi-Fi provides the bandwidth necessary for transmitting real-time sensor data, including high-resolution thermal images from the centralized stand, which is not feasible with low-power, long-range alternatives like LoRa or Zigbee.

Ease of Integration: The ESP8266 Wi-Fi module is easy to set up and integrates seamlessly with cloud platforms for remote data access. This simplifies development and allows for real-time data monitoring.

Sufficient Range for Small Deployments: For the current setup, the 5-meter communication radius is well within Wi-Fi's range, ensuring reliable connectivity between Agri-cones and the centralized hub without requiring additional infrastructure.

Experimental Efficiency: Wi-Fi enables rapid prototyping and testing, ideal for laboratory research and small-scale field trials, where quick setup and easy access to data are more important than long-range communication.

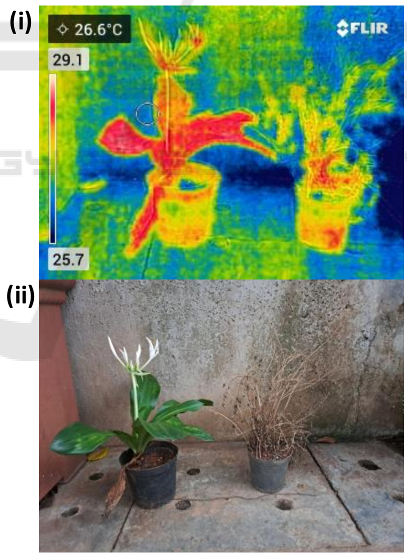

Figure 6: (i) Thermal image of a dead plant alongside an alive plant and (ii) the corresponding color image.

2.4 System Architecture and Communication

This system is specifically designed for laboratory research and experimental purposes, as well as small-scale field deployments. The current configuration, with two Agri-cones per square meter and a 5-meter communication radius from the centralized hub, allows for precise environmental monitoring in smaller areas. The setup enables researchers to validate the system's performance before scaling it to larger fields or more complex deployments. The use of Wi-Fi provides easy integration for real-time data collection and simplifies the testing process in these controlled settings.

Sensor Data Collection: Each Agri-cone collects environmental data from its attached sensors. The DHT11 measures humidity, the soil moisture sensor detects water levels, and the MQ9 and MQ135 gas sensors monitor CO_2, methane, and ammonia levels. The ESP8266 microcontroller processes the sensor readings locally, performing initial filtering and aggregation.

Data Transmission: Using Wi-Fi, the ESP8266 sends the pre-processed data to the Centralized Camera Stand at intervals. The communication occurs within a 5-meter radius, ensuring reliable transmission from all Agri-cones in the area. This distance is ideal for small-scale experiments and offers sufficient coverage for small agricultural plots or lab setups.

Centralized Processing: The Raspberry Pi 5 at the stand collects and processes the incoming data from all Agri-cones in the network. It aggregates sensor readings, performs anomaly detection (e.g., detecting abnormal gas levels), and integrates the thermal camera's data to monitor plant health. The thermal camera captures infrared images, helping to detect unhealthy plants or non-functional Agri-cones.

Data Visualization: The processed data is displayed in real-time on a custom dashboard, allowing the user to monitor environmental conditions and receive alerts for anomalies. This system supports real-time decision-making, vital for applications like precision farming or experimental trials.

3 DATA COLLECTION AND RESULTS

3.1 Agri-Cones

The Agri-Guard system's sensors provide environmental data, including temperature, soil moisture, humidity, and gas concentrations (CO_2, CH_4, & NH_4).

These readings are plotted on a graph to visualize changes over time (Figure 8). Upon adding manure to the soil, notable changes in sensor readings are observed. The gas sensor MQ9, which detects CO_2 and methane, shows a significant increase due to the organic matter decomposition in the manure. Concurrently, the added water raises the humidity and soil moisture levels, which is reflected in their respective sensor readings. Similarly, over time, as microbial decay progresses, the MQ135 sensor, which measures ammonia levels, also shows a slight increase, indicating the breakdown of organic nitrogen compounds in the manure.These dynamic changes are plotted and compared with those from the control setup (Figure 8), where the control lacks manure addition, unlike the experimental setup.

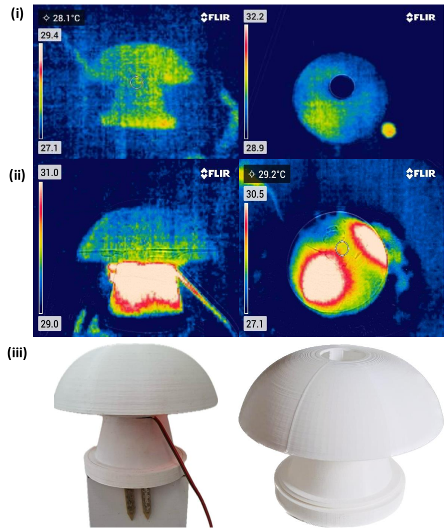

Figure 7: Thermal image of the Agri-Cone when it is (i) switched off, (ii) switched on and (iii) the corresponding original color image.

3.2 Centralized Camera Stand

The Agri-Guard system employs advanced thermal imaging technology to monitor plant health and the functionality of Agri-cones. The thermal images captured by the FLIR C3-X Compact thermal camera provide a detailed heatmap of the monitored area, which is then analyzed to determine the status of plants and Agri-cones. This section explains the process and effectiveness of using thermal imaging in conjunction with a classification model to achieve accurate monitoring results. The thermal images obtained from the camera display variations in temperature across the monitored field. Living plants exhibit distinct thermal heatmaps characterized by larger areas of red, indicating higher temperatures due to active biological processes such as photosynthesis and respiration. These processes generate heat, which is captured by the thermal camera, resulting in a prominent red coloration on the heatmap (Figure 6). Conversely, dead plants lack these active processes, leading to a cooler temperature profile that appears in the

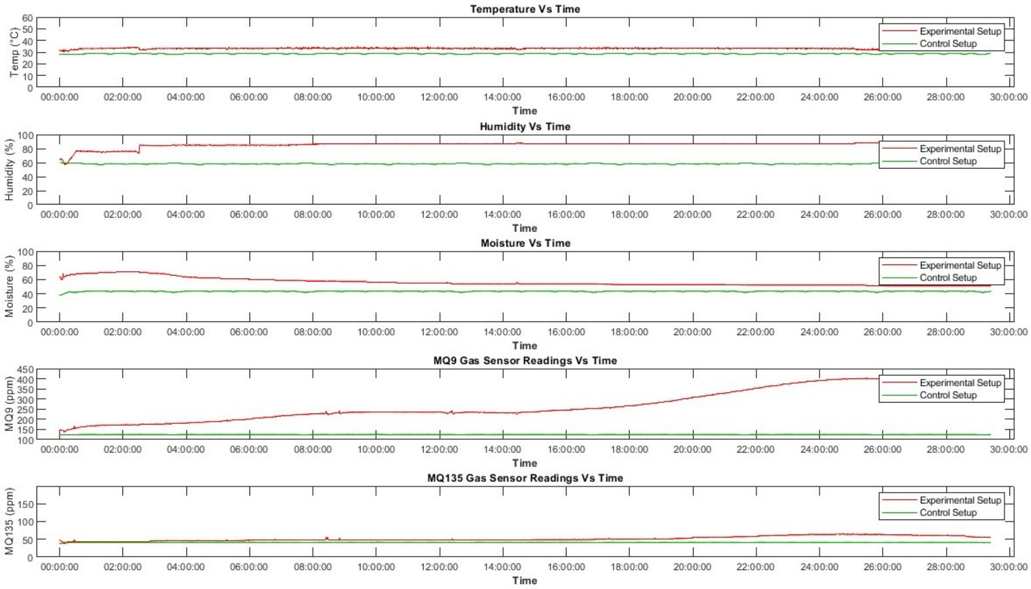

Figure 8: Agri-cone sensor measurements over time showing graphs before addition of manure and water (Control), and after adding the organic manure and water (Experimental).

lower spectrum of the heatmap, typically represented by blue and green colors. To classify whether a plant is dead or alive, the thermal images are fed into a classification model. Numerous binary classification models were evaluated for this task, including logistic regression, support vector machines (SVM), and Decision trees. However, it was found that a region-based Convolutional Neural Network (R-CNN) provided the best performance. The R-CNN model was particularly effective due to its ability to analyze specific regions within the thermal images, focusing on areas of interest and providing a more accurate classification. The R-CNN model achieved an overall accuracy of 92.7%, significantly outperforming other models investigated. The accuracy of all the models investigated is listed in Table 1. In addition to plant

Table 1: Accuracy of models investigated for classifying between dead and alive plant for a thermal image.

Model Name	Accuracy
R-CNN	**92.7%**
Decision Tree	89.9%
SVM	82.4%
Logistic Regression	80.1%

health monitoring, the thermal images are also used to assess the functionality of the Agri-cones. Functional Agri-cones generate heat due to the active circuitry inside, which is reflected in their thermal heatmap as a higher concentration of red and green colors. These colors indicate the heat produced by the electronic components in operation. On the other hand, Agri-cones that are switched off or malfunctioning show a lack of heat generation, appearing in the lower spectrum of the thermal heatmap with cooler colors such as blue and green (Figure 7). The classification model used for Agri-cone functionality also leverages the region-based CNN approach giving 100% classification accuracy. This model effectively distinguishes between operational and non-operational Agri-cones by analyzing the thermal signature of each device. The higher concentration of warm colors in the heatmap corresponds to active, powered-on Agri-cones, while the absence of such colors indicates a non-functional state.

3.3 Power Management and Battery Life Analysis

The Agri-cone system is powered by two 3.7V, 4000mAh Li-Po batteries in series, providing a total of 7.4V with a combined capacity of 4000mAh. The following section provides a detailed analysis of the power consumption and battery life based on the components used and the operating conditions. The active components of each Agri-cone include the Wemos D1 Mini (ESP8266), DHT11 humidity sensor, soil moisture sensor, and gas sensors (MQ9, MQ135). The Wemos D1 Mini ESP8266 is characterized for operating current of 170 mA at 3.3V. Hence for a higher voltage of 7.4V, equivalent current of 75.8mA is drawn.

The other components including DHT11 Humidity Sensor, Soil Moisture Sensor, MQ9 Gas Sensor, and MQ135 Gas Sensor draws current of 0.3mA, 35mA, 150mA, and 56mA respectively. The total current consumption during active operation is estimated to be 317.1 mA. The total power consumption in active mode is estimated to be 2.3475 W.

With a 4000mAh battery, the device would last approximately for Battery Life (Active) $= \frac{4000\,\text{mAh}}{317.1\,\text{mA}} \approx 12.61\,\text{hours}$ To extend the battery life, a duty cycle is implemented where the device remains active for 10% of the time and in deep sleep (where power consumption is minimal) for the remaining 90%, where the current drawn in sleep state is 0.02mA. The average time weighted current drawn by the device is thus computed as per the Equation 1.

$$\text{Average Current} = \begin{array}{l}(0.1 \times 317.1\,\text{mA})+ \\ (0.9 \times 0.02\,\text{mA}) = 31.73\,\text{mA}\end{array} \tag{1}$$

The corresponding power consumption with the duty cycle is: $P_{\text{avg}} = 31.73\,\text{mA} \times 7.4\,\text{V} = 0.2348\,\text{W}$ The battery life with deep sleep mode enabled is thus given by: Battery Life (Sleep Mode) $\approx \frac{4000\,\text{mAh}}{31.73\,\text{mA}} \approx 126\,\text{hours}$ This battery optimization allows the system to operate for approximately 126 hours (over 5 days) between charging, making it ideal for small-scale field experiments where continuous monitoring is required without frequent battery changes.

4 CONCLUSION

The Agri-Guard system represents a significant leap in precision agriculture by combining thermal imaging with R-CNN classification to provide accurate, real-time monitoring of plant health and the operational status of agricultural equipment. Leveraging the FLIR C3-X Compact thermal camera, Agri-Guard effectively differentiates between healthy and distressed plants through distinct thermal signatures, while identifying functional and non-functional equipment based on heat patterns. Its modular design, optimized power management, and Wi-Fi-enabled data transmission to enhance adaptability for laboratory and field applications.

Future advancements will improve scalability, refine long-term deployment strategies, and integrate additional functionalities, enabling broader applications across diverse agricultural contexts. By addressing these areas, Agri-Guard has the potential to drive substantial improvements in resource management, crop yield monitoring, and sustainable agricultural practices.

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