A Data-Driven Drone System for Efficient Crop Monitoring and Sustainable Farming

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***Abstract*—** This paper presents the experimental evaluation and performance analysis of CropCare+, a drone-assisted precision agriculture system designed for real-time crop monitoring and automated intervention. The proposed system integrates aerial crop health assessment, targeted pesticide and water spraying, soil moisture sensing, and automated irrigation control into a unified platform. Building upon the system architecture introduced in the previous work, this study focuses on the machine learning dataset, model training, hardware implementation, and field-level performance validation. A lightweight convolutional neural network model was trained on a labeled crop image dataset to classify plant conditions such as healthy growth, pest infestation, disease symptoms, and water stress. The trained model was deployed on a Raspberry Pi-based onboard unit using edge inference, enabling real-time decision-making during drone operation. Simultaneously, an ESP32-based ground unit monitored soil moisture and environmental parameters to control irrigation through a threshold-based mechanism. Experimental tests were conducted in a controlled field environment to evaluate classification accuracy, resource utilization, and system responsiveness. The results demonstrate improved detection accuracy, reduced water and pesticide usage, and faster response times compared to conventional manual methods. The integrated approach significantly reduces labor requirements while enabling data-driven, localized interventions. The findings confirm the practical feasibility of the CropCare+ system as a scalable, cost-effective solution for intelligent and sustainable precision agriculture.

***Index Term*—** *drone technology, health monitor, pesticide sprinkling, water supply automation..*

I. INTRODUCTION

Precision agriculture has emerged as a critical approach to addressing the growing global demand for food while minimizing environmental impact and resource consumption. Traditional farming practices often rely on manual monitoring, uniform pesticide spraying, and fixed irrigation schedules, which can lead to inefficient resource utilization, delayed disease detection, and increased operational costs. With the rapid advancement of unmanned aerial vehicles (UAVs), embedded systems, and machine learning, modern agricultural systems are increasingly shifting toward intelligent, data-driven solutions that enable real-time decision-making and targeted interventions.

In recent years, drone-assisted agricultural systems have demonstrated significant potential in tasks such as crop monitoring, pesticide spraying, and remote sensing. However, many existing solutions focus on isolated functionalities, such as aerial spraying or offline crop analysis, without integrating real-time health monitoring, automated irrigation control, and on-device intelligence into a unified system. This limitation reduces the overall effectiveness of precision farming and restricts the ability to perform timely, localized interventions.

In the previous work, CropCare+ was proposed as an integrated drone-assisted precision agriculture platform that combines targeted pesticide and water spraying, real-time crop health monitoring using onboard image processing, soil moisture sensing, and automated irrigation control through a ground-based unit. The system employs a quadcopter equipped with a Raspberry Pi and camera for edge-based machine learning inference, while an ESP32-based ground unit manages environmental sensing and irrigation actuation. The integrated architecture aims to reduce manual labor, minimize chemical and water wastage, and enhance decision-making through real-time field data.

While the initial work established the system architecture, hardware design, and operational workflow, a detailed experimental evaluation is necessary to validate the system's performance in practical agricultural scenarios. Specifically, the effectiveness of the machine learning model, the efficiency of resource utilization, and the responsiveness of the automated control mechanisms must be quantitatively assessed to determine the feasibility of the proposed approach.

Therefore, this paper presents the experimental validation and performance analysis of the CropCare+ system. It focuses on the dataset used for crop health classification, model training and deployment on edge hardware, hardware implementation details, and field testing procedures. The system is evaluated in terms of classification accuracy, water and pesticide usage efficiency, and response time of automated interventions. Comparative analysis with conventional farming practices is also conducted to demonstrate the advantages of the proposed approach.

The results presented in this study provide practical insights into the performance, reliability, and scalability of the CropCare+ system, establishing its potential as a cost-effective and intelligent solution for modern precision agriculture.

II. Summary of Proposed System

2.1 Overview of CropCare+ Architecture

The CropCare+ system is an integrated drone-assisted precision agriculture platform designed for real-time crop monitoring and automated intervention. The system consists of two primary units: a drone-based aerial unit and a ground-based sensing and control unit.

The aerial unit is built on a quadcopter frame equipped with an APM 2.8 flight controller, brushless DC motors, electronic speed controllers, and a lithium-polymer battery for stable flight operations. A Raspberry Pi 4, interfaced with an RGB camera, performs real-time crop image acquisition and edge-based machine learning inference to detect plant conditions such as disease, pest infestation, or water stress. The drone also includes dual liquid tanks connected to mini-pumps and solenoid valves, enabling targeted spraying of water or pesticides based on detected crop conditions.

The ground unit is developed using an ESP32 microcontroller connected to soil moisture, temperature, and humidity sensors. This unit continuously monitors environmental parameters and controls irrigation through a relay-driven sprinkler system. When soil moisture drops below a predefined threshold, the system automatically activates irrigation to maintain optimal soil conditions. Communication between the aerial and ground units enables coordinated decision-making and real-time monitoring through a remote dashboard.

2.2 Key Contributions of Paper 1

The first paper primarily focused on the design and development of the CropCare+ system. Its key contributions include:

- Development of an integrated drone platform capable of aerial monitoring and targeted spraying.
- Implementation of real-time crop health analysis using edge-based machine learning on a Raspberry Pi.
- Design of an ESP32-based ground unit for soil moisture sensing and automated irrigation control.
- Integration of aerial and ground units for coordinated, data-driven farm management.
- Development of a prototype system demonstrating reduced manual labor and improved resource efficiency.

While Paper 1 emphasized system architecture and operational workflow, the present study focuses on dataset preparation, hardware implementation details, and experimental performance evaluation.

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III. Machine Learning Dataset and Model Details

3.1 Dataset Description

The machine learning model was trained using a combination of the PlantVillage dataset and a supplementary real-world leaf image dataset. The PlantVillage dataset is a widely used benchmark dataset for plant disease classification and contains high-quality images captured under controlled conditions. It includes 38 distinct classes representing healthy and diseased leaves across multiple crop species.

However, models trained solely on PlantVillage data often suffer from limited generalization due to the uniform backgrounds and controlled imaging conditions. To enhance robustness and simulate real agricultural environments, an additional dataset consisting of field-style leaf images was incorporated. This dataset contains images captured under natural lighting conditions, variable backgrounds, and realistic noise.

Figure 1. Sample plant leaf images from the PlantVillage dataset

To align with real-world deployment objectives, the original disease-specific classes were mapped into broader stress categories, namely:

- Healthy
- Fungal Disease
- Bacterial Disease
- Viral Disease
- Nutrient Deficiency
- Water Stress

This category-based formulation reduces over-specialization and improves the model's ability to generalize across unseen disease variations.

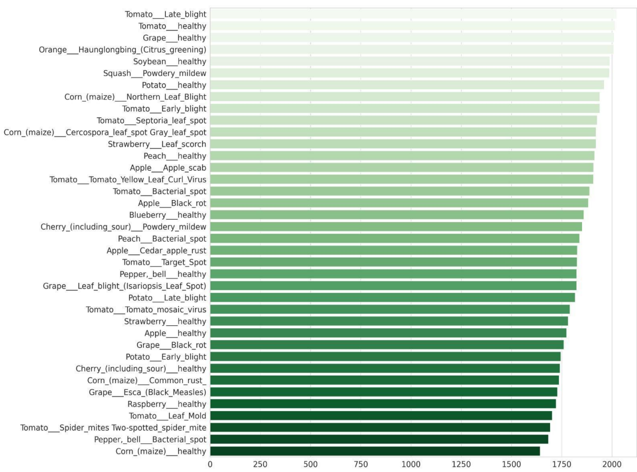

Fig.2. Dataset Description.

3.2 Data Preprocessing

Data Augmentation

To simulate real-world variability, extensive augmentation techniques were applied during training. These transformations expose the model to diverse visual conditions, including variations in lighting, orientation, and scale.

The augmentation pipeline included:

- Random Resized Cropping
- Horizontal and Vertical Flipping
- Random Rotation
- Color Jittering (brightness, contrast, saturation)
- Gaussian Blurring

These transformations significantly improve the model's robustness to:

- Background variations
- Illumination changes
- Camera noise
- Leaf orientation differences

Normalization

Images were converted into tensor representations and scaled to standard pixel intensity ranges, enabling stable gradient updates during training.

Label Remapping

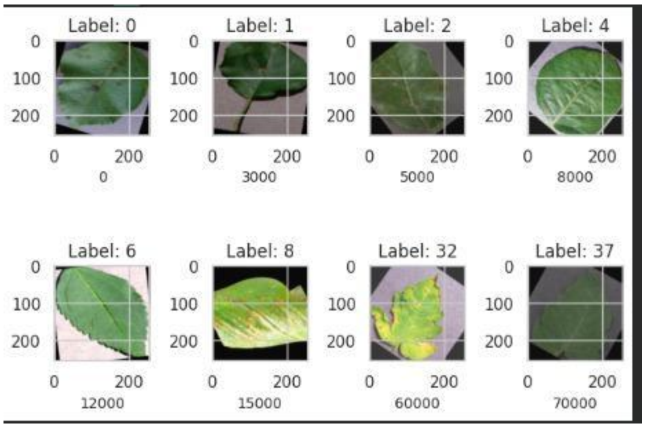

Fig.3. Labelling

Instead of retaining the original 38 disease classes, labels were systematically remapped into six agricultural stress categories. This preprocessing step simplifies the classification task while preserving biologically meaningful distinctions.

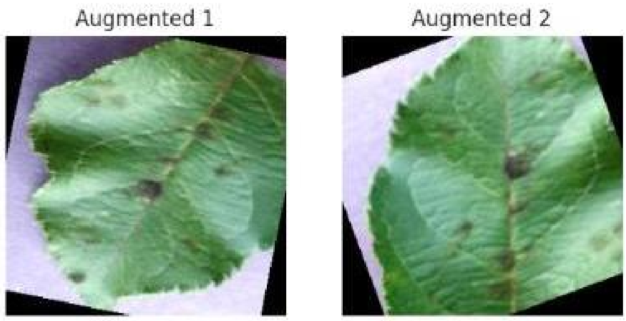

Fig.4. Augmentation

3.3 Model Architecture and Training

The plant stress classification system was implemented using a deep convolutional neural network based on the ResNet18 architecture. Residual Networks are widely used in image classification tasks due to their ability to mitigate the vanishing gradient problem through the use of identity shortcut connections. These residual connections allow deeper networks to be trained effectively by enabling gradients to flow directly through the network, thereby improving convergence and overall performance.

In this work, a transfer learning approach was adopted to leverage the pre-trained weights of ResNet18 trained on the ImageNet dataset. The use of transfer learning enables the model to utilize previously learned low-level and mid-level visual features such as edges, textures, shapes, and patterns, which are common across most image datasets. This significantly reduces training time and improves generalization performance, especially when the available agricultural dataset is relatively smaller or heterogeneous.

The original fully connected classification layer of the pre-trained ResNet18 model was replaced with a new dense layer corresponding to the six defined stress categories: Healthy, Fungal, Bacterial, Viral, Nutrient, and Water stress. This modification allows the network to adapt its learned features specifically to the agricultural classification task.

The training process was carried out in two stages to ensure stable learning and effective feature adaptation. In the first stage, the convolutional backbone of the ResNet18 model was frozen, and only the final classification layer was trained. This stage allowed the model to learn category-specific decision boundaries without altering the pre-trained feature extractors. In the second stage, the deeper layers of the network were selectively unfrozen and fine-tuned using a lower learning rate. This fine-tuning stage enabled the network to adapt its higher-level feature representations to plant disease characteristics while maintaining the robustness of the pre-trained features.

The model was trained using the cross-entropy loss function, which is commonly used for multi-class classification problems. The Adam optimizer was employed to update the network parameters due to its adaptive learning rate and efficient convergence properties. An initial learning rate of 10^{-3} was used during the classification layer training stage, and a reduced learning rate of 10^{-4} was applied during the fine-tuning stage to prevent large parameter updates.

Training was performed using mini-batch gradient descent with a batch size of 32 images. The number of epochs was selected empirically based on validation performance to avoid overfitting. During training, the model's performance was monitored using validation accuracy and loss metrics.

To enhance reliability during deployment, a confidence-based prediction mechanism was incorporated. The model outputs class probabilities using a softmax function, and predictions below a predefined confidence threshold are labeled as uncertain. This mechanism helps reduce incorrect classifications and ensures safer decision-making in practical agricultural environments.

Overall, the combination of transfer learning, staged fine-tuning, and confidence-based filtering enabled the model to achieve robust performance across both controlled and real-world agricultural image conditions.

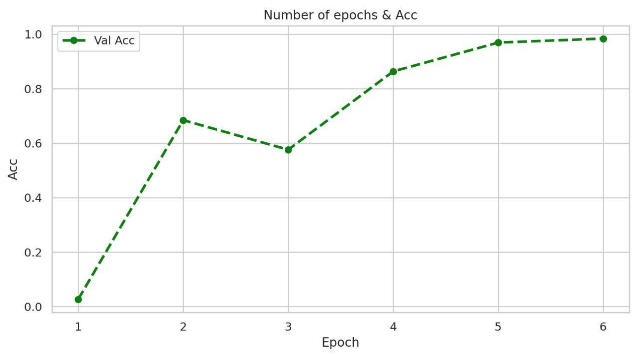

Fig.5.Number of Epochs & Accuracy.

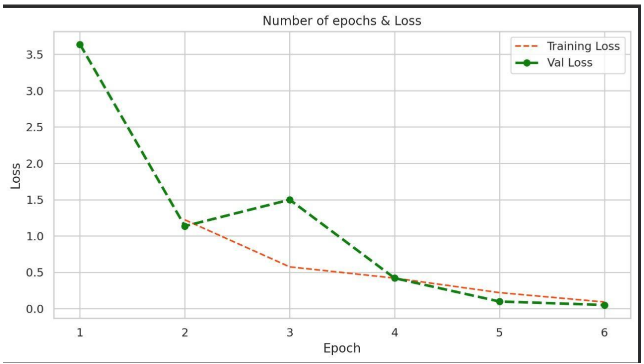

Fig.6. Number of Epochs & Loss

IV. Hardware Implementation And Setup

4.1 Hardware components

The proposed CropCare+ system consists of two major hardware subsystems: the drone-based aerial monitoring unit and the ground-based environmental monitoring unit. These two subsystems work together to enable real-time crop health monitoring and automated agricultural intervention.

Drone-Based Monitoring Unit

The aerial monitoring platform is built using a quadcopter drone equipped with multiple components for flight control, image acquisition, and automated spraying. The drone is controlled using the APM 2.8 flight controller, which acts as the primary navigation and stabilization unit. The flight controller processes sensor inputs such as accelerometer, gyroscope, and GPS data to maintain stable flight and allow autonomous navigation over agricultural fields.

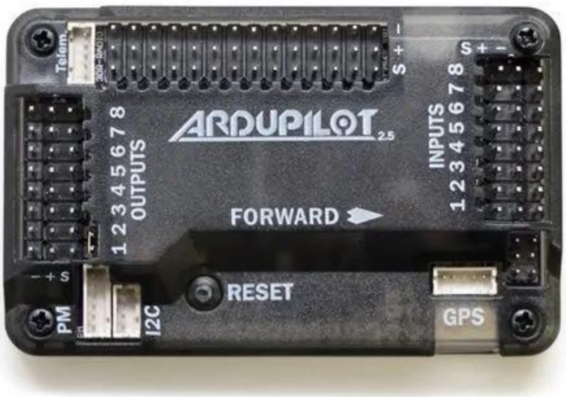

Fig.7. APM 2.8 Ardupilot

The drone is powered by a high-capacity lithium polymer (Li-Po) battery, which provides sufficient power for the propulsion system, onboard electronics, and spraying mechanism. The propulsion system consists of brushless DC motors and electronic speed controllers (ESCs), which enable controlled lift and maneuverability during field operation.

A Raspberry Pi board is integrated into the drone as the onboard processing unit. The Raspberry Pi is responsible for managing image acquisition and coordinating the spraying mechanism. A Pi Camera module connected to the Raspberry Pi captures high-resolution images of crop leaves during flight. These images are used by the machine learning model to identify plant health conditions and detect potential diseases or stress symptoms.

Fig.8. Raspberry PI

To enable targeted intervention, the drone includes a dual spraying system controlled through relay modules. Two separate relay-controlled pump mechanisms are connected to different liquid tanks. One tank contains water for irrigation, while the other contains pesticide or fertilizer solution. Based on the classification results generated by the machine learning system, the Raspberry Pi activates the appropriate relay to trigger the required spraying mechanism. This enables precise and selective treatment of affected plants while minimizing chemical usage.

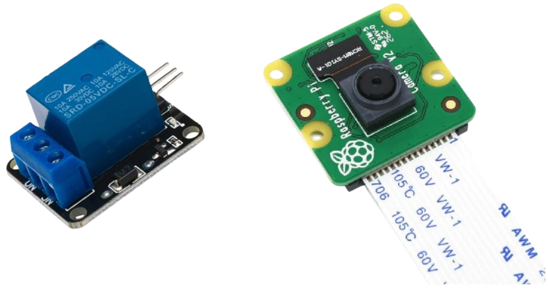

Fig.9. Relay & Camera Module

Ground-Based Monitoring Unit

In addition to aerial monitoring, the system includes a ground-based sensing unit designed to continuously monitor environmental and soil conditions. This subsystem collects real-time agricultural data that assists in irrigation management and crop health assessment.

The ground unit consists of multiple sensors deployed within the crop field, including:

- Soil moisture sensors to measure water content in the soil
- Temperature sensors to monitor ambient environmental conditions
- Soil nutrient sensors to estimate nutrient availability in the soil

These sensors continuously collect environmental data and transmit the readings to a Raspberry Pi processing unit installed at the ground station. The Raspberry Pi processes the incoming sensor data and determines whether irrigation or other interventions are required.

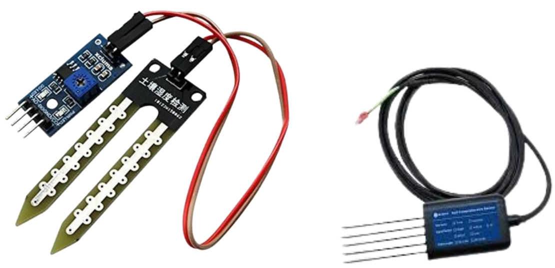

Fig.10. Moisture & Nutrient Sensors

Communication Module (GSM Integration)

To enable remote monitoring and real-time alert transmission, a GSM communication module is integrated into the CropCare+ system. The GSM module provides wireless communication capabilities using cellular networks, allowing the system to send important notifications to the farmer's mobile device.

The GSM module is connected to the Raspberry Pi processing unit through serial communication, enabling the system to transmit messages whenever significant agricultural events occur. These events include plant disease detection, irrigation activation, abnormal soil conditions, or system status updates.

When the machine learning model detects a diseased plant, the Raspberry Pi processes the classification result and activates the pesticide spraying mechanism. Simultaneously, the GSM module can transmit an alert message to the farmer indicating the detected crop condition and the action taken by the system. Similarly, when soil moisture levels drop below the predefined threshold and the irrigation system is activated, the GSM module can notify the farmer about the irrigation process.

The integration of the GSM module enhances the system by providing remote communication and monitoring capabilities, allowing farmers to receive updates about crop health and irrigation status even when they are not physically present in the field. This feature improves the usability and reliability of the CropCare+ system in real-world agricultural environments.

Fig.11 GSM900A Module

4.2 Field Test Enviroment

The field testing of the proposed CropCare+ system was conducted in a real agricultural environment to evaluate the performance of the integrated drone-based crop monitoring and automated intervention system. During the experimental phase, the trained machine learning model was tested on various types of plant leaves collected from different crop plants. These samples included both healthy leaves and leaves affected by different plant diseases to assess the classification capability of the model under realistic conditions.

The drone-mounted imaging system captured images of plant leaves using the onboard Pi Camera while flying over the crop area. These images were processed by the Raspberry Pi, where the trained machine learning model analyzed the leaf patterns and classified the plant condition into the predefined stress or disease categories. When the system detected a diseased plant, the drone automatically activated the pesticide spraying mechanism through a relay-controlled pump system. The pesticide stored in the onboard tank was then sprayed directly onto the affected plants, enabling targeted and efficient treatment.

In addition to aerial monitoring, the system also collected ground-level environmental data using sensors deployed within the agricultural field. These sensors measured parameters such as soil moisture, temperature, and soil nutrient levels. The collected sensor data was transmitted to the Raspberry Pi processing unit, which analyzed the conditions to determine whether irrigation was required.

If the soil moisture level dropped below a predefined threshold, the system automatically activated the irrigation mechanism through relay-controlled pumps. In cases where localized watering was required, the drone performed precision water spraying directly over the affected crop areas. This combination of aerial pesticide spraying and automated irrigation allowed the system to perform intelligent crop management while minimizing water and chemical usage.

The experimental evaluation demonstrated that the integrated system could effectively detect plant diseases, automate pesticide application, and manage irrigation based on real-time environmental data, thereby supporting precision agriculture practices.

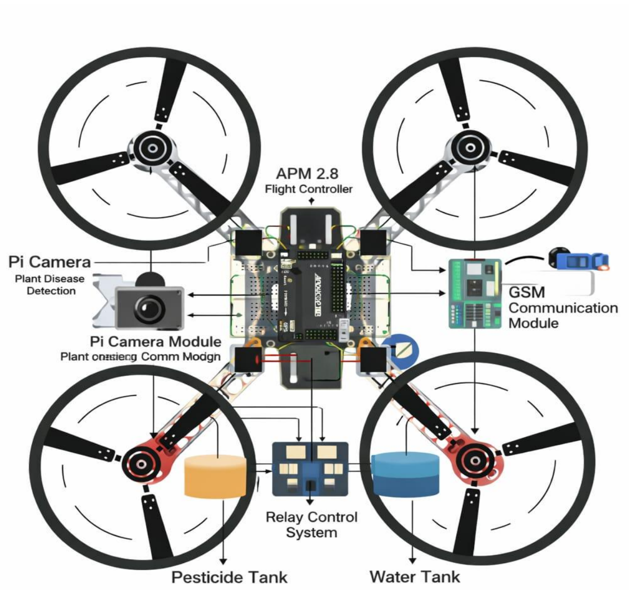

Fig.12. Drone Setup

V. System Parameters

The proposed smart agriculture system integrates ground-level environmental sensing with drone-based crop monitoring to enable intelligent irrigation and disease management. Soil conditions are monitored using sensors connected to an ESP microcontroller placed at ground level, while aerial monitoring and pesticide spraying are handled by a drone platform equipped with a Raspberry Pi and camera system.

Sensor data collected from the field is transmitted wirelessly to the drone using LoRa communication, allowing the onboard system to make irrigation and spraying decisions based on real-time environmental conditions and machine learning predictions. System parameters define the thresholds used to trigger irrigation and spraying actions in order to optimize water usage and minimize unnecessary chemical application.

5.1 Irrigation Threshold Logic

The irrigation subsystem uses a soil moisture sensor connected to an ESP microcontroller to monitor the water content in the soil. The ESP module periodically reads soil humidity values and transmits the data to the drone's Raspberry Pi using LoRa communication.

Fig.13. LORA Module

The irrigation control logic is based on predefined soil moisture thresholds that indicate different soil conditions. When the soil moisture level falls below 30%, the soil is considered excessively dry and immediate irrigation is required. In this case, the ESP controller directly activates the ground irrigation pump through a relay module to deliver water to the crops.

When the soil moisture level rises above 60%, the soil is considered sufficiently hydrated. In this condition, additional irrigation is not required. However, if aerial watering is necessary for broader crop coverage, the drone can activate a sprinkler-based irrigation system mounted on the drone platform.

The decision process operates as follows:

* Soil moisture is continuously monitored using ground sensors.
* Sensor data is transmitted to the drone using LoRa communication.
* If moisture < 30%, the ESP activates ground irrigation pumps.
* If moisture ≥ 60%, the drone-based sprinkler system may be used for light irrigation across larger areas.

This dual irrigation approach allows the system to combine localized ground irrigation with aerial sprinkler support, ensuring efficient water distribution and improved crop hydration management.

5.2 Spraying Control Parameters

The spraying subsystem operates on the drone platform and is triggered based on plant disease predictions generated by the onboard machine learning model. The drone captures leaf images using the Pi Camera, and the Raspberry Pi processes these images using a trained Convolutional Neural Network (CNN) designed to classify plant health conditions.

The model categorizes plant conditions into six classes:

* Healthy
* Fungal infection
* Bacterial infection
* Viral infection
* Nutrient deficiency
* Water stress

When the model detects fungal, bacterial, or viral infections, the drone activates the pesticide spraying mechanism. To reduce the probability of false detections, a multi-frame verification strategy is implemented. The drone continuously analyzes frames captured during flight, and spraying is triggered only if the disease category is detected consistently across multiple frames with high confidence.

The spraying parameters used in the system are defined as follows:

* Minimum prediction confidence threshold: 0.80
* Minimum consecutive detections required: 5 frames
* Image capture rate: 1 frame per second

Once the conditions are satisfied, the Raspberry Pi sends a signal to activate a relay-controlled pesticide pump connected to the spraying nozzle. The pump operates for approximately 3–5 seconds, allowing pesticide to be sprayed over the affected crop area.

A 10-second cooldown interval is applied between consecutive spraying actions to prevent excessive pesticide usage and allow the drone to reposition for further inspection.

This parameter-driven spraying mechanism enables precision agriculture, where pesticides are applied only to infected regions rather than uniformly across the entire field.

VI. Experimental Results and Analysis

This section presents the experimental evaluation of the proposed CropCare+ system, focusing on the performance of the machine learning model for crop health classification, the efficiency of resource utilization such as water and pesticides, and the response time of the integrated drone and ground monitoring system. The experiments were conducted under practical agricultural conditions to evaluate the reliability and effectiveness of the proposed precision agriculture framework.

6.1 Crop Health Classification Performance

The crop health classification model was evaluated using plant leaf images obtained from the PlantVillage dataset, which contains images of healthy and diseased plant leaves across multiple crop types. The dataset was preprocessed and categorized into four primary classes: Healthy, Fungal, Bacterial, and Viral infections. Image augmentation techniques such as rotation, horizontal flipping, and color jitter were applied to improve the model's generalization capability.

A custom Convolutional Neural Network (CNN) architecture with residual convolution blocks was implemented for plant disease classification. The model was trained using images resized to 224 × 224 resolution with normalization based on ImageNet statistics. The training process utilized the Adam optimizer with a OneCycle learning rate schedule, and class-weighted cross-entropy loss was applied to handle class imbalance.

The model was trained for 8 epochs and achieved a final validation accuracy of 98.3%, demonstrating strong capability in distinguishing between healthy and diseased plant leaves. The trained model successfully detected disease patterns such as leaf discoloration, fungal spots, and viral leaf curl symptoms across different plant species.

During real-time operation, images captured using the drone-mounted Raspberry Pi camera were processed by the trained CNN model deployed on the edge computing unit. The inference pipeline classified each captured leaf image into one of the four predefined categories. Experimental testing showed that the system could reliably detect infected plants under varying natural lighting conditions and background environments.

The classification output was directly integrated with the drone's pesticide spraying mechanism. When the system detected a diseased plant, the drone automatically activated the relay-controlled pesticide pump, enabling targeted spraying. This integration allowed the system to perform real-time disease detection and automated treatment, demonstrating the feasibility of the proposed CropCare+ system for intelligent crop monitoring.

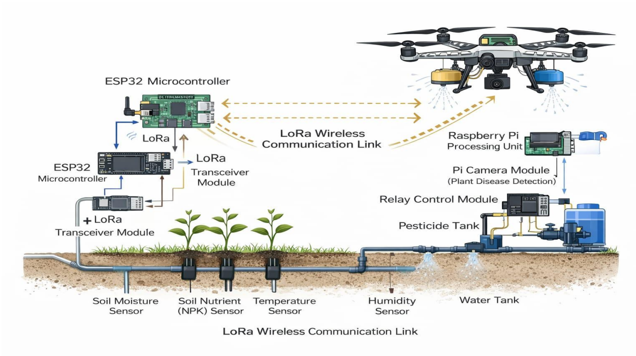

Fig.14. CNN-based crop disease detection pipeline used in the CropCare+ system.

6.2 Water and Pesticide Usage Analysis

The CropCare+ system was designed to reduce unnecessary usage of water and pesticides through data-driven precision agriculture techniques. In conventional farming practices, irrigation and pesticide spraying are often applied uniformly across large crop areas, resulting in inefficient resource utilization and increased environmental impact.

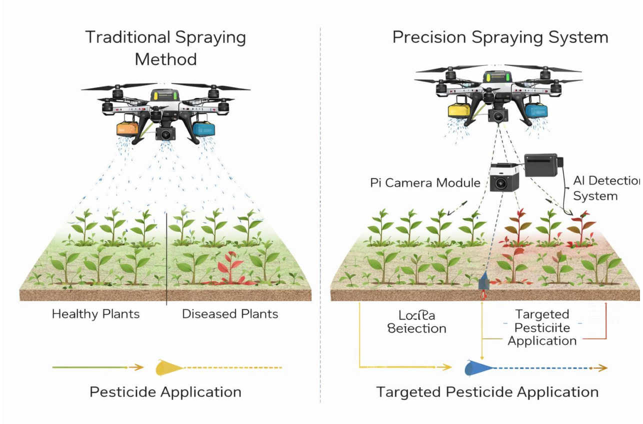

Fig.15. Traditional Method versus Precision Spraying Method

In contrast, the proposed system performs targeted pesticide application based on disease detection results from the CNN model. When the model identifies a diseased plant, the drone activates the pesticide spraying mechanism only in the affected region. This selective spraying approach significantly reduces chemical consumption by avoiding unnecessary pesticide application across healthy crop areas.

Experimental field simulations demonstrated that the system successfully limited pesticide spraying to the detected infected regions, thereby minimizing chemical waste and reducing potential soil and water contamination.

In addition to disease detection, irrigation management was implemented using soil moisture sensors connected to an ESP-based control unit. Soil moisture data was continuously monitored, and irrigation pumps were automatically activated when the moisture level dropped below a predefined threshold. For localized irrigation requirements, the drone was also capable of performing precision water spraying over specific crop zones.

The experimental results indicate that the CropCare+ system can effectively optimize water and pesticide usage, improving agricultural resource efficiency while supporting environmentally sustainable farming practices.

6.3 System Latency and Response Time

The system latency and response time were evaluated to measure the time required for the system to detect plant diseases and initiate the corresponding treatment actions. The response time was measured from the moment the drone captured a plant leaf image to the activation of the pesticide spraying mechanism.

The experimental results show that the system operates efficiently within a short processing interval. The edge computing unit performs image acquisition, preprocessing, CNN inference, and control signal generation in a streamlined pipeline. The trained CNN model performs inference rapidly, allowing the system to classify crop health conditions in near real-time.

Once a disease is detected, the classification output triggers the relay-controlled spraying mechanism, activating the pesticide pump with minimal delay. This rapid response enables immediate treatment of infected plants and helps prevent further disease spread within the crop field.

Similarly, the irrigation subsystem demonstrated quick response times through continuous soil moisture monitoring. When soil moisture levels dropped below the defined threshold, the irrigation pump was automatically activated to restore optimal soil conditions.

Overall, the experimental analysis confirms that the integrated drone-based monitoring system combined with edge AI and IoT sensors provides fast and reliable responses for both crop disease treatment and irrigation management. This capability makes the proposed CropCare+ system well suited for real-time precision agriculture applications.

VII. Limitations and Challenges

While the proposed CropCare+ system demonstrates significant potential for improving precision agriculture through the integration of drone technology, machine learning, and IoT-based sensing, several limitations and operational challenges were identified during the development and testing phases of the system.

One of the primary limitations of the system lies in the dependency of the machine learning model on the diversity and quality of the training dataset. The model was trained using a combination of curated plant disease datasets and real-world leaf images; however, agricultural environments present a wide range of disease variations that may not be fully represented in the training data. As a result, the system may face difficulties in accurately identifying previously unseen diseases or rare plant stress conditions. Additionally, variations in lighting conditions, shadows, leaf occlusion, and background noise can affect the accuracy of image-based disease classification when images are captured during drone flights.

Another significant challenge involves image acquisition during aerial operation. Drone-based monitoring introduces several environmental variables that can impact image quality. Factors such as wind disturbances, vibration of the drone, rapid movement, and variations in flight altitude may result in blurred or partially captured images. These factors can reduce the reliability of the machine learning inference process. Maintaining stable drone navigation and consistent image capture conditions is therefore essential for achieving reliable crop monitoring performance.

The computational limitations of the onboard processing unit also present certain constraints. The Raspberry Pi serves as the primary processing unit for image acquisition, data processing, and system control. While it is capable of running lightweight machine learning models, complex deep learning architectures may increase computational load and inference time. This limitation can affect the overall system latency, particularly when the drone is required to process large volumes of images during continuous field monitoring.

Another challenge is associated with the accuracy and reliability of ground-based sensors used for environmental monitoring. Soil moisture sensors, temperature sensors, and nutrient detection sensors are sensitive to environmental factors such as soil composition, humidity variations, and sensor placement. Inaccurate calibration or environmental interference may result in incorrect sensor readings. Such inaccuracies could lead to inefficient irrigation decisions or incorrect assessments of soil conditions.

The integration of multiple hardware subsystems also introduces system complexity. The proposed architecture combines drone navigation systems, machine learning models, IoT sensors, communication modules, and relay-controlled actuators. Ensuring seamless communication between these components is critical for reliable operation. Communication delays, hardware failures, or synchronization issues between the drone system and ground monitoring unit may affect the responsiveness of automated actions such as pesticide spraying or irrigation control.

Furthermore, the operational scalability of the system remains a challenge for large-scale agricultural deployments. While the prototype system performs effectively in small or medium-sized experimental fields, monitoring very large agricultural areas would require multiple drones, improved flight endurance, and advanced coordination mechanisms. Battery limitations of drones also restrict continuous operation time, which may affect the feasibility of large-scale field coverage.

VIII. Future Enhancements

Although the proposed CropCare+ system demonstrates effective integration of drone-based monitoring, machine learning–based crop disease detection, and IoT-based environmental sensing, several improvements can be implemented in future versions to further enhance system performance, scalability, and reliability in real-world agricultural environments.

One major enhancement involves expanding the dataset used for training the machine learning model. Currently, the model is trained using a combination of publicly available plant disease datasets and real leaf images. However, incorporating a larger and more diverse dataset containing different crop species, disease variations, and environmental conditions can significantly improve the model's robustness and accuracy. This would allow the system to identify a broader range of plant diseases and stress conditions in different agricultural regions.

Another potential improvement is the use of more advanced deep learning architectures and edge computing hardware. Lightweight yet powerful models such as EfficientNet or MobileNet could be deployed along with dedicated AI accelerators to improve real-time image processing capabilities. This would reduce inference time and allow faster disease detection during drone flights.

The LoRa-based communication system, currently used for transmitting environmental sensor data from the ground unit to the central processing system, can also be expanded further. LoRa technology provides long-range, low-power communication, which is highly suitable for large agricultural fields. Future versions of the system could implement a LoRa sensor network with multiple distributed sensor nodes, allowing large-scale monitoring of soil moisture, temperature, and nutrient levels across extensive farmland.

The drone system can also be enhanced by implementing intelligent autonomous navigation algorithms. Instead of following fixed flight paths, future drones could dynamically adjust their flight trajectory based on crop health information collected during previous scans. This would allow the drone to focus on high-risk areas and reduce unnecessary monitoring of healthy regions.

Another promising improvement is the integration of multispectral or hyperspectral imaging sensors. Unlike standard RGB cameras, multispectral cameras can detect subtle changes in plant reflectance that indicate early signs of stress, nutrient deficiency, or disease. This would allow earlier detection of crop problems before visible symptoms appear.

Future versions of the system may also incorporate predictive irrigation management using data analytics. By combining soil sensor data, historical environmental records, and weather forecasts, the system could automatically determine optimal irrigation schedules. This predictive approach would further improve water management efficiency and reduce agricultural resource wastage.

Additionally, the system could be scaled using multiple coordinated drones operating simultaneously. A drone swarm architecture could significantly increase coverage area and reduce monitoring time for large-scale agricultural farms.

Finally, integrating the system with cloud-based agricultural monitoring platforms would allow farmers to remotely access crop health reports, sensor data, and field analytics through mobile applications or web dashboards. This would enable better decision-making and long-term crop management.

Overall, these future enhancements would improve the intelligence, efficiency, and scalability of the CropCare+ system, enabling it to support next-generation precision agriculture and sustainable farming practices.

IX CONCLUSION

This paper presented the design and implementation of CropCare+, an integrated precision agriculture system that combines drone technology, machine learning–based crop disease detection, and IoT-enabled environmental monitoring to improve agricultural efficiency. The proposed system utilizes a drone platform equipped with a camera and relay-controlled spraying mechanism to monitor crop health and perform targeted pesticide and water spraying. In addition to aerial monitoring, a ground-based sensing system was implemented using multiple environmental sensors to continuously measure parameters such as soil moisture, temperature, and nutrient levels.

The captured leaf images are processed using a trained machine learning model capable of classifying plant health conditions and identifying diseased crops. When a disease is detected, the system automatically activates the pesticide spraying mechanism to treat the affected plants. Simultaneously, the ground-based sensor system monitors soil conditions and triggers irrigation when the soil moisture level falls below a predefined threshold. Communication between the ground monitoring unit and the processing system is achieved using LoRa-based wireless transmission, enabling reliable long-range data communication suitable for agricultural environments.

Experimental evaluation demonstrated that the system can effectively identify crop diseases, optimize water and pesticide usage, and automate irrigation based on real-time environmental data. The integration of drone-based monitoring with IoT sensing provides a comprehensive solution for precision agriculture, enabling early detection of plant stress conditions and reducing unnecessary resource consumption.

Overall, the proposed system highlights the potential of combining artificial intelligence, drone technology, and wireless sensor networks to support modern smart farming practices. By enabling automated crop monitoring and targeted agricultural interventions, the CropCare+ system contributes toward improving crop productivity, reducing labor requirements, and promoting sustainable agricultural resource management.

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