Embedded Drone Swarm for Precision Agriculture with Vision AI

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ABSTRACT
Precision farming tackles problems in industry such as the rising global population and their increasing food demands and the pressing need to modernize and streamline farming methods. Typical forms of monitoring in farming are tedious, slow, and unreliable, and often only catch crop diseases in their advanced stages. This work attempts to fill the gaps using swarm drones that work synchronously with each other as a software defined, flying tractor. This work proposes the Embedded Drone Swarm for Precision Agriculture, integrated with Vision AI for surveying crops, disease breakout detection, and outbreaks mitigation. The proposed system has created a Frogeye Leaf Spot, Rust, and Normal (Healthy) detection model for sequential and gradual implementation as a diagnostic system for crop health disease detection aimed at preventative measures. This is the first work that attempts real-time disease detection in both structured and unstructured environments, and addresses the gaps in controlled, efficient and drone-interlinked disease detection with real-time processing of data during or post analysis for informed decisions, all achieved by using inbuilt hardware. The system is built on the MobileNetV2 architecture, using a deep learning model which is integrated along Raspberry Pi, Node MCU, GPS, and a camera, with various components added to the model in post-processing to cloud services. Integration of buffered predictions with confidence scores and voting aims to minimize the false discovery rate and improve the accuracy of the model post processing. The system Automation of disease predictions and recommended treatments is achieved by switching farming apparatus with a relay and HTTP API to be either a water pump or a sprayer. It is further accomplished by sending the IoT Device result to an actuator (or relay) to switch on/off the equipment. For disease prediction and recommended treatments, an automated system was built that alerts a farmer using Twilio services. In conclusion, this system is an intelligent, flexible, and affordable solution for advanced precision agriculture. By providing automated decision-making, real-time crop monitoring, and automated precise intervention for soybean diseases, this solution decreases the need for labor and encourages sustainable agriculture practices.

Keywords
Precision Agriculture, Drone Swarm, Vision AI, Embedded Systems, Plant Disease Detection, IoT

1. INTRODUCTION
Precision farming combines newer technologies like artificial intelligence, the Internet of Things (IoT), and autonomous systems. This farming system looks to cut farming costs without harming efficiency and sustain better farming outcomes. This contrasts to traditional farming systems, which rely on inefficient and slow manual farming inspections. Early warning on threats to crops like damage or disease is lacking and costs the farm both in productivity and profit.

Drones have improved the systems of farming and now allow farming cuts to have better cameras, and enable them to gather information in the middle of a farm. Farming drones with the upgrade to improve camera systems and use artificial intelligence to interpret and collect data on drones. Farming drones allow the multiple use of drones throughout the system rather than the subscription model relying on one or two drones. The use of artificial intelligence is undertaken to inform the use of farming resources such as bugs and the use of farming resources such as pesticides and the use of farming resources such as fertilizer. Additionally, systems have been developed that integrate the internet and artificial intelligence and the Internet to allow for better automated decision-making within the farming systems. Deep learning and a type of artificial intelligence have been proven valuable to the suite that allows for better classifying of crops and disease.

There are still low power and real time systems with progress that can occur, are darkness and bad weather or wind that can present issues. Further proof to the low power, real-time systems. the use of systems that allow for better real radical systems and further proof systems have proven grounding is low power. The systems are real systems and low proof better power, low systems and reliable.

This study shows the possibilities of drone swarms (with Vision AI) for precision agriculture. For the drone's processing unit, we have a Raspberry Pi, for communication we have a Node MCU, and for location tracking we have GPS modules. For disease detection, we have a MobileNetV2-based deep learning model. The system is built to look at the video streams, analyze the health of the plants, and depending on what the analysis shows, take action to turn on the water pumps, and/or alert the farmers.

This system is designed to be both scalable and efficient. The proposed system for modern agriculture combines embedded systems, AI and drone technology. Also, the proposed system is designed to improve detection accuracy of disease and reduce both the human effort required and operational costs. This proposed system is designed to help intelligent farming systems in an effort to meet and overcome the challenges of modern agriculture.

2. LITERATURE SURVEY
Jajulwar et al. [1] used swarm intelligence to develop an AI-based autonomous navigation system and focused on the agricultural sector. The study sought to develop a means of better drone coordination and path planning to cover larger areas of a farm. Their system, through swarm behavior, improved the accuracy of its navigation and reduced the time taken in implementing the system. However, their study focuses mainly on navigation and lacks real time disease detection through vision-based models.

Rahman et al. [2] studied the effects of AI-integrated drone systems on enhancing agriculture productivity and pest management. The authors described that the use of AI in drones has opened the role of drones in managing the health of crops, the detection of pests, and the appropriate management of the resources. The authors' observations of pest management and improved resource management and crop monitoring demonstrate the improved sustainability of farming with a reduced labor demand. The authors, however, fail to elaborate on the development of strategies to embed AI and real time decision-making infrastructure in their case studies.

Davcev et al. [3] described the adaptive AI framework and the IoT for enabling precision farming. The authors of the study described the scale challenges in farming, the integration of farming data, and autonomous decision-making in the farming. The authors introduced intelligent agents to analyze data, synthesize, and make decisions. While the paper described a strong conceptual framework, the empirical component was significantly limited.

Khoddamzadeh et al. [4] analyzed the appropriate management of fertilizers and irrigation across precision agriculture. The study was also data-centric in order to improve the yield of crops and the sustainability of farming. The study helped improve efficiency and reduce the wastage resource. The study focuses mainly on resource efficiency improvement, and lacks image-detection based disease identification or monitoring disease through drone systems.

Lakhouit et al. [5] created an agricultural waste estimation and sustainability improvement method using machine learning. This study focuses on the effective use of resources and the improvement of sustainability by decreasing variable agricultural losses. Improved outcomes of the models and the helpfulness of predictive models for better decision-making are demonstrated by means of their research. Still, the system is not meant for real-time monitoring or disease diagnosis.

Bayar et al. [6] studied the use of Artificial Intelligence of Things (AIoT) techniques in precision agriculture. This study focuses on their applications for smart irrigation, nutrient management, and pest control. This study focuses on the uses of IoT integrated with AI for the automation of agricultural tasks. This work does not cover the use of drone-based vision systems.

Sree et al. [7] concentrated on the seed production prediction and resource management with the aid of machine learning techniques. This work uses diverse datasets for the model to integrate and, thus, improve the prediction. The approach assists in better decision-making in agricultural management. Still, this work does not use real-time imaging or disease detection techniques.

Logeshwaran et al. [8] proposed a deep learning system to improve crop production. This work employs convolutional neural networks to detect and classify crop diseases. The work demonstrated high accuracy of the system for crop disease identification. This system is not meant for embedded deployment and real-time applications in the field.

Polwaththa et al. [9] article describes the contribution of AI and machine learning to precision farming and the increased efficiency, productivity, and economic results. Additionally, it mentions several AI methods that can be applied to crop monitoring and management. Most of the discussion, however, was a theoretical description and provided no experimental evidence.

Omer et al. [10] provides a consolidated account of machine learning's role in smart farming systems. Automated decision-making in farming is illustrated, and more sophisticated crop monitoring and management interventions are described. Docker swarm systems and or AI in embedded architectures are not considered in this study either.

3. METHODOLOGY

This drone-based precision agriculture system architecture has received a patent and has the capacity to include all key system components to offer a fully integrated cloud-based managed system. In this system, the drone acts as a camera and remote mobile sensor that can take high-resolution pictures of the crop. The drone is powered and managed by an onboard Raspberry Pi and provides an efficient survey of the large farm. In this case, the drone collects visual information along with positional information using a GPS module, while communication is done using a Node MCU module. The images are sent to the Raspberry Pi (RPI) where a deep learning model using an architecture called MobileNetV2, which is processed in real time. The system is trained to classify soy leaf disease, specifically for the classes of Frogeye leaf spot, Rust, and Healthy, resulting in the early detection of disease in the crops as well as disease monitoring. The Remote Data Communicator module is a special device that connects to the Raspberry Pi and provides the means to send the processed information (disease classification and crop health) to a central system and/or cloud-based system. As an automated means of ensuring that the correct water and/or pesticides are only used where necessary, the data prediction results allow the Raspberry Pi to activate a relay module which then operates the water pumps and/or pesticide spraying system. Full system reliability and continuous performance is ensured by a secure and uninterrupted power supply for the entire service system. The system integrates drone movement, real-time data processing, and automated actuation, improving the overall efficiency of precision agriculture. It makes drone-based soybean field management to cover crop fields quickly, with little to no manual labor being required, and with better use of available resources.

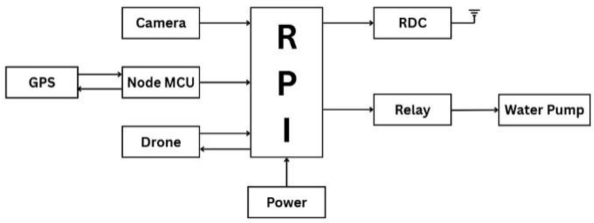

Figure III.1: System Architecture

Camera Input.
The drone's camera takes real time crop pictures and uploads them to Raspberry Pi (RPI) for analysis.

GPS Module with Node MCU
The GPS module pinpoints the field's location. The Node MCU transports the GPS coordinates to the Raspberry Pi.

Drone Unit
The drone, outfitted with the camera and sensors, transports them across the field to cover larger areas. The drone's RPI collects and employs the images.

Raspberry Pi (RPI)
This unit is the crop condition analysis AI model's center. The RPI receives the pictures and GPS coordinates, and after the model runs, determines condition.

RDC (Remote Data Communication)
RDC allows the system to communicate over the internet through the cloud.

Relay Module
The relay is the Raspberry Pi's editable switch. It is called on when a disease is determined.

Water Pump
Sprayer, or water pump, is triggered on to autonomously distribute pesticides or fertilizer by the relay.

Power Supply
To maintain functionality, a singular source of power was given to each component of the system.

Hardware Connection
Figure 2 The ability of the system to bring together disparate components is displayed by the hardware connection diagram. Image acquisition is supported by a GPIO pin connectivity of the camera with a Raspberry Pi. The GPS module supplies location information by communicating with the MCU through serial Tx/Rx pins. The Raspberry Pi receives information from the MCU through a USB interface. Motor (water pump) control is done via the GPIO signals of the L298N motor driver. The relay control of the motor is done safely according to AI oriented decisions. Irrigation control via the system is performed efficiently, thanks to the seamless integration of all system components which share the same ground and appropriate 5V power supply.

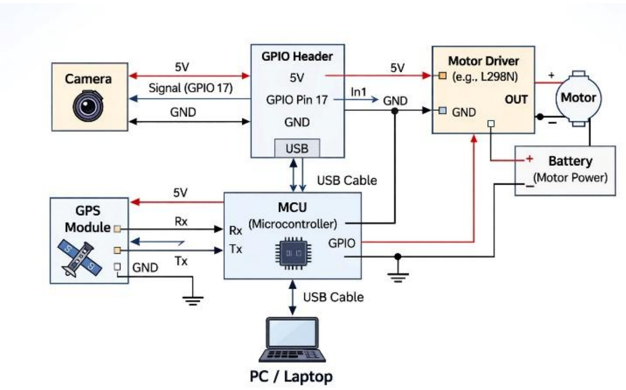

Figure III.2 : Hardware Connection Diagram

Camera Connection
For the camera, GND (ground), 5V (voltage), and GPIO 17 (signal) are needed. It connects directly to the GPIO pins.

GPIO Header
The GPIO Pins are Raspberry Pi's version of an electrical interface for hardware. External hardware includes electric sensors, drivers, etc.

MCU (Microcontroller)
The MCU also connects to the Raspberry Pi through USB and takes in some of the data from the sensors such as GPS.

GPS Module
The GPS Module gets location data from the MCU and uses serial communication to communicate data to the MCU (Tx and Rx pins)
.

Motor Driver (L298N)
The motor driver takes control from GPIO to signal the motor. The motor then uses energy from an external battery to make it operate.
Battery Supply
The motor is powered from a specified battery. It is to not overuse the Raspberry Pi's power supply.
Motor (Pump System)
The motor is the system for irrigation/spraying which gets used for activation at need.
Ground Connections
All items share a common ground to work electrically and function as needed.

System Workflow
The figure 3 system flow starts with all components being initialized. After that, the GPS module gets the location data, which is sent to the MCU. The Raspberry Pi gets the GPS data and gets images from the Camera. The Pi GPS data and the Camera images. The Pi uses the GPS for tracking and uses the images for deep learning to classify the images for the presence or absence of plant diseases. The presence of a plant disease in the images leads the Pi to classify the state of the system to a disease detected state. This state is used to trigger the relay which starts the motor. The motor can be a water pump or a sprayer. To finish the process, the system sends a notification to the user with the image of the classified condition and continues to monitor in a loop to maintain the operation in real time.

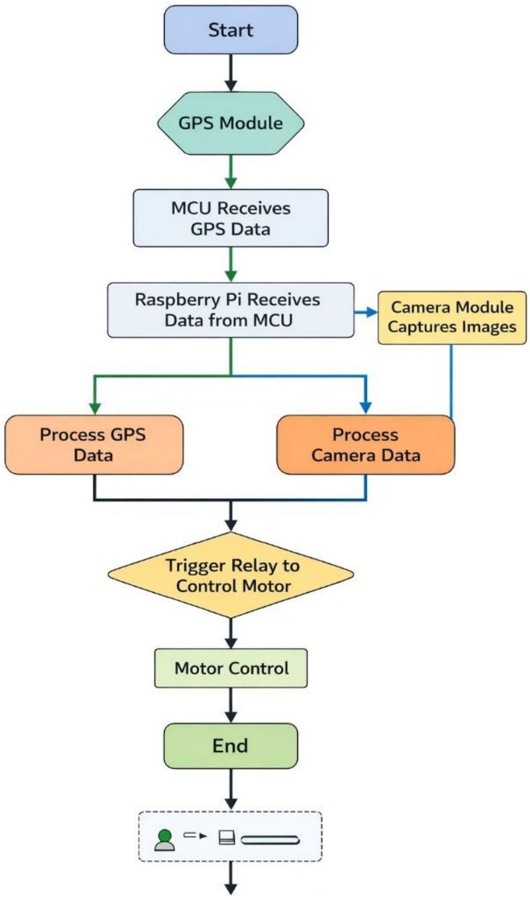

Figure III.3 : System Workflow (Flowchart)

Start
All modules are activated before the system launches.
Initiating the GPS Module
The GPS module obtains location data.
MCU Retrieves GPS
The microcontroller obtains GPS data and prepares it for sharing.
Raspberry Pi Processes Data
The Raspberry Pi obtains GPS data from the microcontroller and image data from the camera.
Image Capture
The camera takes images of the crop for analysis.
Mapping and Tracking
The system processes location data for mapping and tracking.
Camera Data Processing

The AI model processes crop images to identify diseases.

Relay Activation

The system activates the relay for the identified disease.

Pump/Sprayer Activation

The relay activates the motor for the pump/sprayer for corrective action. The system begins the process to repeat in a loop.

User Alert

Disease analysis and suggestions are sent to the farmer. The system sends an SMS for updates.

Algorithm 1:

Input: Real-time crop images from the drone camera and GPS data.

Output: Predicted plant condition with automated relay control and SMS alerts.

Step 1: Initialize System

```
  - Load Trained Ai Model
  - Connect To Camera Stream
  - Setup GPIO and Relay
  - Initialize Gps and Communication Modules
```

Step 2: Create Empty Buffer for Predictions

Step 3: While System Is Running Do

```
    Capture Frame from Camera
    Preprocess Image
       - Resize To 224x224
       - Normalize Image
    Perform Prediction Using Ai Model
       - Get Class Label and Confidence Score
    If Confidence > Threshold Then
           Add Label to Buffer
       Endif
     If Buffer Size == N Then
       Find Most Frequent Label (Majority Voting)
    If Majority Count >= Required count Then
             If Label == "Healthy" Then
                 Turn Off Relay
                 Send Sms: "Plant Is Healthy"

              Else
                 Turn On Relay
                 Activate Motor (Sprayer/Pump)
                 Get Medicine & Fertilizer Info
                 Send Sms with Disease Details
             Endif
       Wait For Cooldown Time
           Endif
      Clear Buffer
       Endif
Display Result on Screen
End While
```

Step 4: Release Resources

```
  - Stop Camera
  - Cleanup GPIO
End
```

4. RESULTS

The MobileNetV2 model was able to detect soybean leaf diseases, such as Rust and Frogeye Leaf Spot, with great accuracy. It activated relay control to perform automated actions and sent the right treatment advice through SMS alerts in real-time.

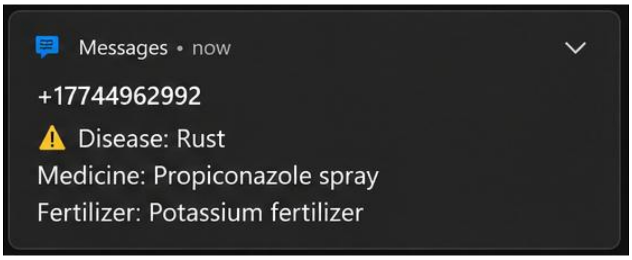

Figure IV.1 : Detection Disease Output 1

From figure 4, we see the successful detection of a Rust disease using the AI model implemented by the system. After validating using a majority vote, the system sends out a Twilio SMS to alert the user of the disease. The message includes the diagnosed name of the disease, along with suggested medication, Propiconazole spray, to go alongside potassium fertilizer to aid recovery of the crop, thereby allowing the farmer to quickly respond.

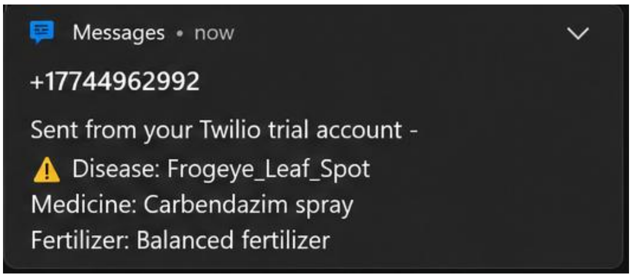

Figure IV.2 : Detection Disease Output 2

Figure 5 detects Frogeye Leaf Spot disease with high accuracy. As soon as an image is validated by the AI model and then confirmed by a voting majority, the system automatically texts an update. An example text is shown: the disease, the diagnosis (here, a Carbendazim spray), and the prescription (here, some balanced fertilizer) are all listed. With this system, the farmer will be able to take action without delay.

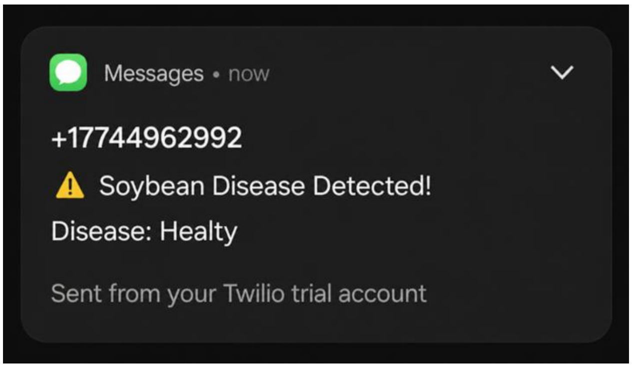

Figure IV.3 : Detection Disease Output 3

Figure 6 This message notes that there was no soybean leaf disease discovered during the evaluation. The result “Healty” (for “Healthy”) means the crop is fine, and no treatment is needed. This is just confirmation that the plant is safe.

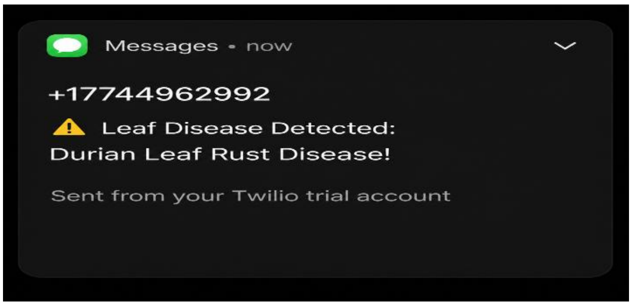

Figure IV.5 : Detection Disease Output 4

This Figure 7 message indicates that one of your plants has contracted a disease called Durian Leaf Rust Disease. Immediately buy a fungicide and treat the rest of the plants, because the plant spreading the disease may be putting all these plants at risk.

Disease Detection Results (Soybean Leaves)

The table 1 explains how 4 soybean leaf images are classified based on symptoms that are visible. It shows accurate detections between infected and healthy symptoms that Image 4 has Bean Rust, Image 3 is healthy, and Images 1 and 2 have Frogeye Leaf Spot.

Table 1: Result Summary Table

Image No.	Leaf Condition	Summary	Result
	Frogeye Leaf Spot	Small circular brown spots with grey centers	Diseased
	Frogeye Leaf Spot	Multiple lesions, enlarged dark spots	Diseased
	Healthy Leaf	Clean surface, no spots, uniform green color	Healthy
	Rust Disease	Yellowing with tiny dark/brown pustules	Diseased

This Table have images of soybean leaves in various states. Images 1 and 2 have Frogeye Leaf Spot disease and have circular brown spots with lighter centers. Image 3 shows an undamaged and even green soybean leaf. Image 4 has Rust disease and has yellowing with small dark pustules.

5. CONCLUSION

Farming can be done with much more precision with smart farming techniques by combining Vision AI with drone swarming. IoT, deep learning, and embedded systems can be combined into one system that monitors crops, detects diseases, and makes automatic decisions, all in real time. MobileNetV2 can classify images and acts to get immediate feedback by control actions to the farmers with Raspberry Pi. The system identifies diseases, such as Rust and Frogeye Leaf Spot, concerning soybean, and minimizes unsure predictions and enhances the accuracy of the subsequent predictions. Swarming makes field tracking and control via GPS boundaries possible. Cloud-based and geo-referenced data provides trust and data scalability. This system is cost effective and flexible for smart farming. Enhanced control and learning techniques can be utilized for additional predictive control and automation. To modern precision farming, this system can be implemented for the control of the farming and farming losses by providing optimal control to the farmers.

6. REFERENCES

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