GHANA AI HACKATON COMPETITION

CREATE | INNOVATE | DOMINATE

Precision Agriculture: AI, IoT, and WLAN-Enabled Crop Monitoring and Disease Detection in Ghana's Agricultural Sector

JULY 2025

TEAM MEMBERS

Abdul Rahman Abubakar
BSc. Computer Engineering
Ashesi University

Salia Abdul-Mumin
BSc. Electrical Engineering
Ashesi University

CHALLENGES IN GHANA'S AGRICULTURE INDUSTRY

- Ghana's agriculture faces persistent challenges from crop diseases, climate change, and inefficient farming practices.
- Traditional methods lack timely, data-driven detection, leading to late interventions, improper treatments, and reduced yields.
- Many farmers have limited access to modern tools and training, making it difficult to respond effectively to emerging threats.

AI-POWERED SOLUTION

- Our AI-powered solution leverages drones, smartphones, soil sensors, and machine learning to detect diseases in five key crops: Cashew, Cassava, Maize, Lettuce, and Tomato in real time.
- This affordable and accessible tool empowers farmers to diagnose diseases early, apply appropriate treatments, and improve productivity.
- The system also provides insights and recommendations to help farmers mitigate these challenges.

PROBLEM STATEMENT

Traditional farming methods are inefficient in managing resources and detecting diseases, resulting in poor crop health and low productivity. We aim to create a lightweight, user-friendly AI model deployable via smartphones and drones, supported by IoT and machine learning, to enhance real-time crop monitoring across cashew, cassava, maize, lettuce, and tomato.

OBJECTIVES

- Develop an integrated system combining IoT sensors, drones, and machine learning to detect crop diseases at early stages.
- Optimize resource use, especially water and fertilizer.
- Improve crop yield and health through real-time monitoring.
- Ensure accuracy, low inference time, and small memory footprint.
- Develop a user-friendly mobile app to display all relevant information
- Minimize environmental impacts through precise interventions.
- Leverage WLAN infrastructure to enable seamless communication between IoT devices, drones, and mobile apps for real-time data sharing and system responsiveness.

SYSTEM REQUIREMENTS

Functional Requirements

- Continuous soil data collection via IoT sensors
- Drone-based image capture of crops
- Real-time integration and processing on Raspberry Pi
- ML model for disease detection and irrigation scheduling
- Mobile app for displaying insights, alerts, and historical data
- Notifications for critical events (e.g., low moisture, disease presence)
- WLAN-enabled communication layer to support local data exchange between sensors, drones, and mobile devices without reliance on constant internet access.

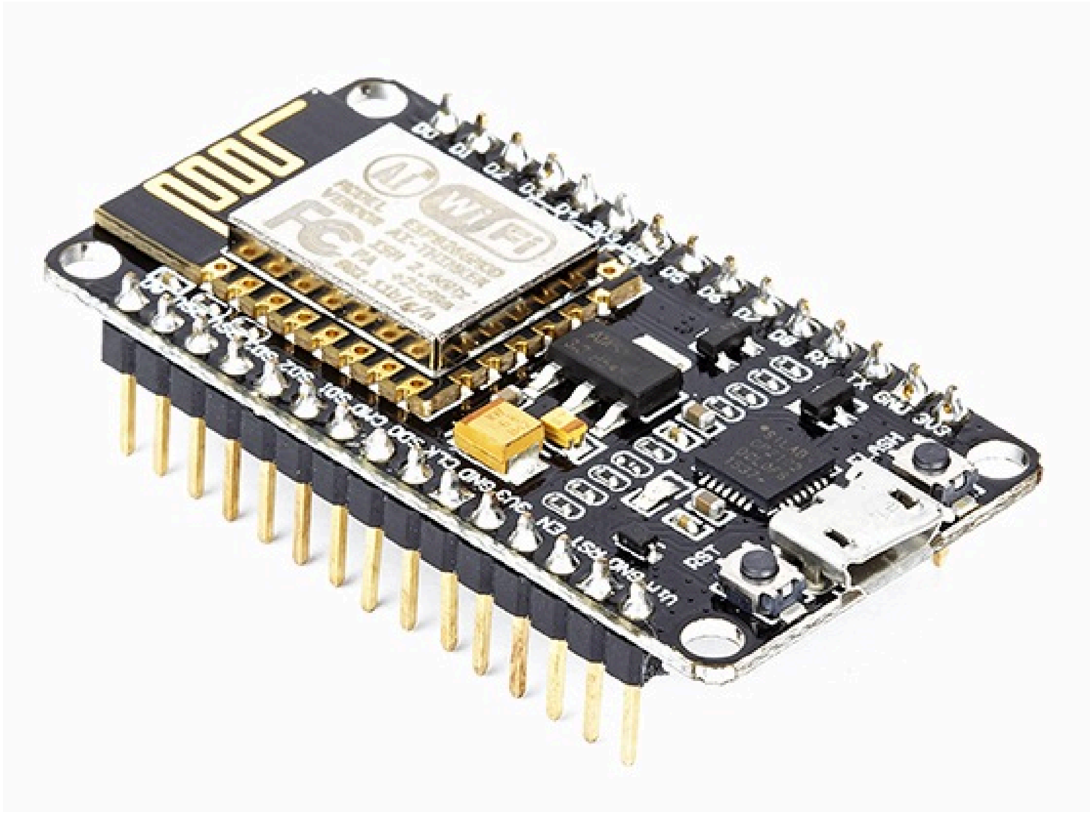
SYSTEM REQUIREMENTS

Non-Functional Requirements

- Low Latency: Near real-time data transmission and analysis
- Accuracy: High prediction precision in disease detection
- Energy Efficiency: Battery-powered hardware optimized for field use
- Ease of Use: Intuitive mobile app requiring minimal farmer training
- Robustness: Durable hardware to withstand farm conditions
- Reliable Connectivity: Maintain stable communication across system components via WLAN, even in low-infrastructure rural areas.

ELECTRONICS COMPONENTS SELECTION

ESP8266



Reason for choosing ESP8266

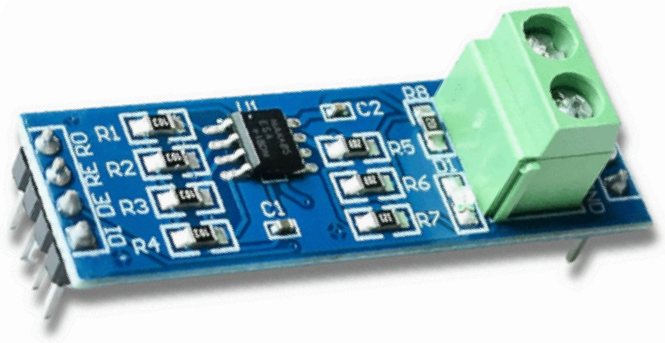
- Low cost
- In-built WiFi chip with full TCP/IP stack
- Low powered

HALISENSE SOIL SENSOR

Reason for choosing HaliSense Soil Sensor

- Low cost
- IP rating(IP68) dust-tight & protected against immersion in water
- Accuracy of +/- 0.01
- Operation: 4.5 v

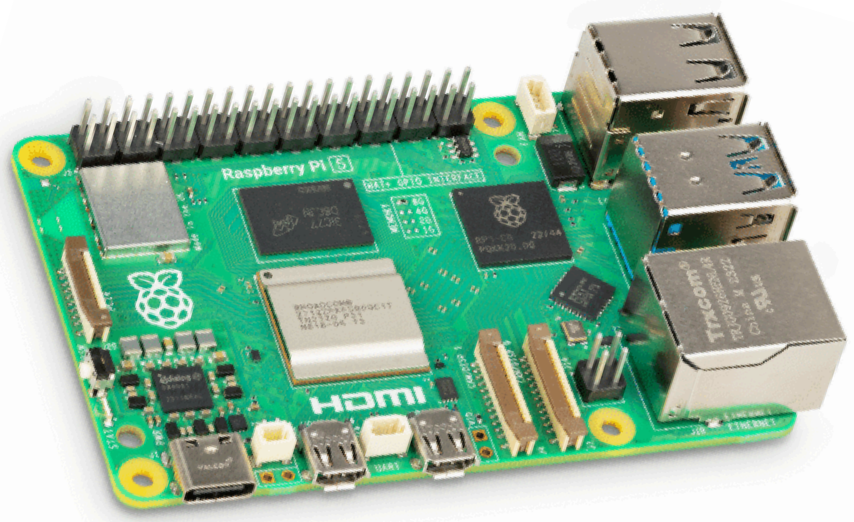
RS485 MODULE



Reason for choosing RS485 Module

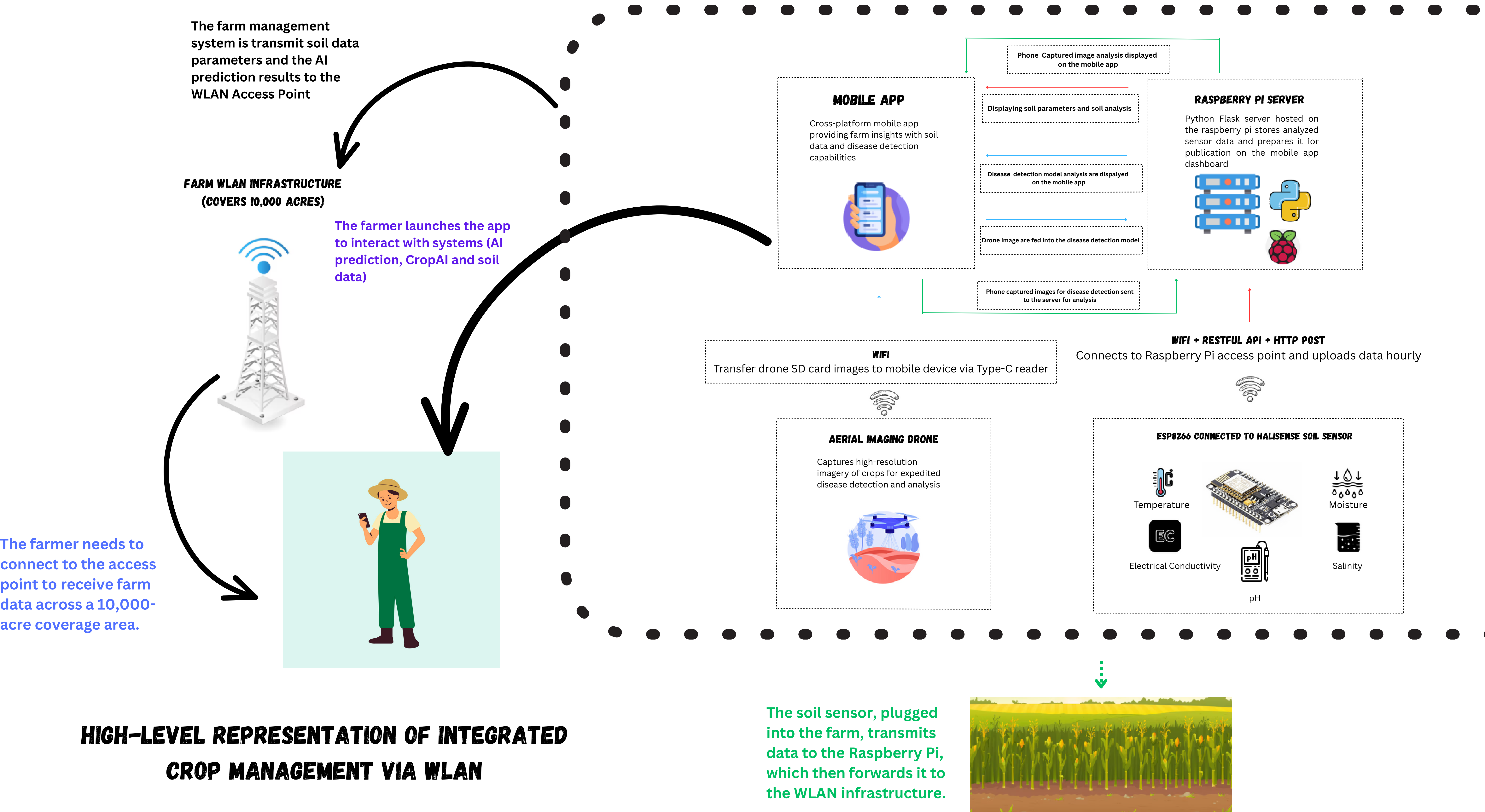
- **Long-Distance Communication (up to 1.2km)**
- **Differential Signaling Standard(Noise Immune)**
- **Multi-Device Networking(up to 32 sensors)**

RASPBERRY PI



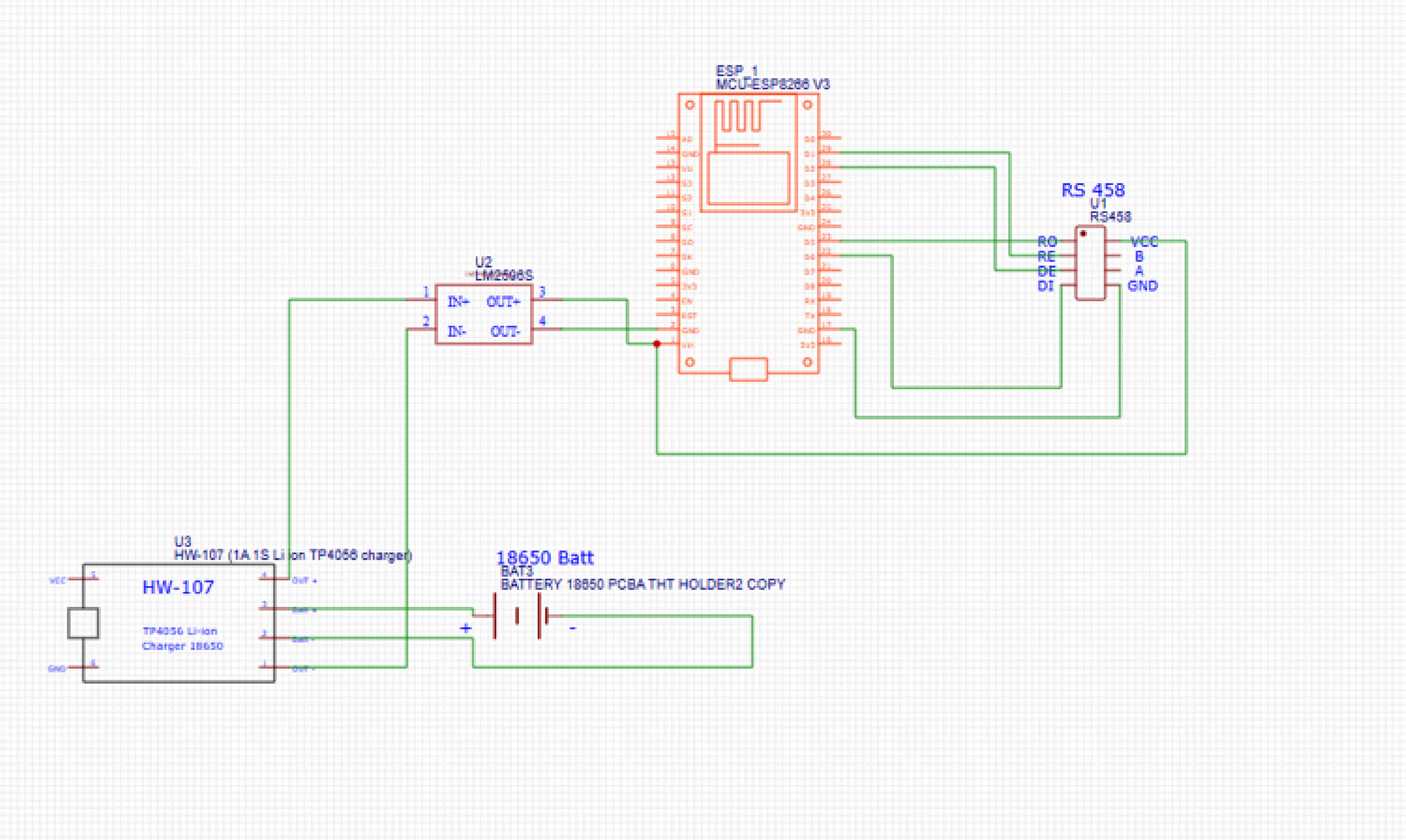
Reason for choosing Rasberry Pi

- Full-Fledged computer (can be server)
- Data Analysis
- Cost-Effective



HIGH-LEVEL REPRESENTATION OF INTEGRATED CROP MANAGEMENT VIA WLAN

SCHEMATIC DIAGRAM OF THE CIRCUIT



PCB DIAGRAM OF THE CIRCUIT

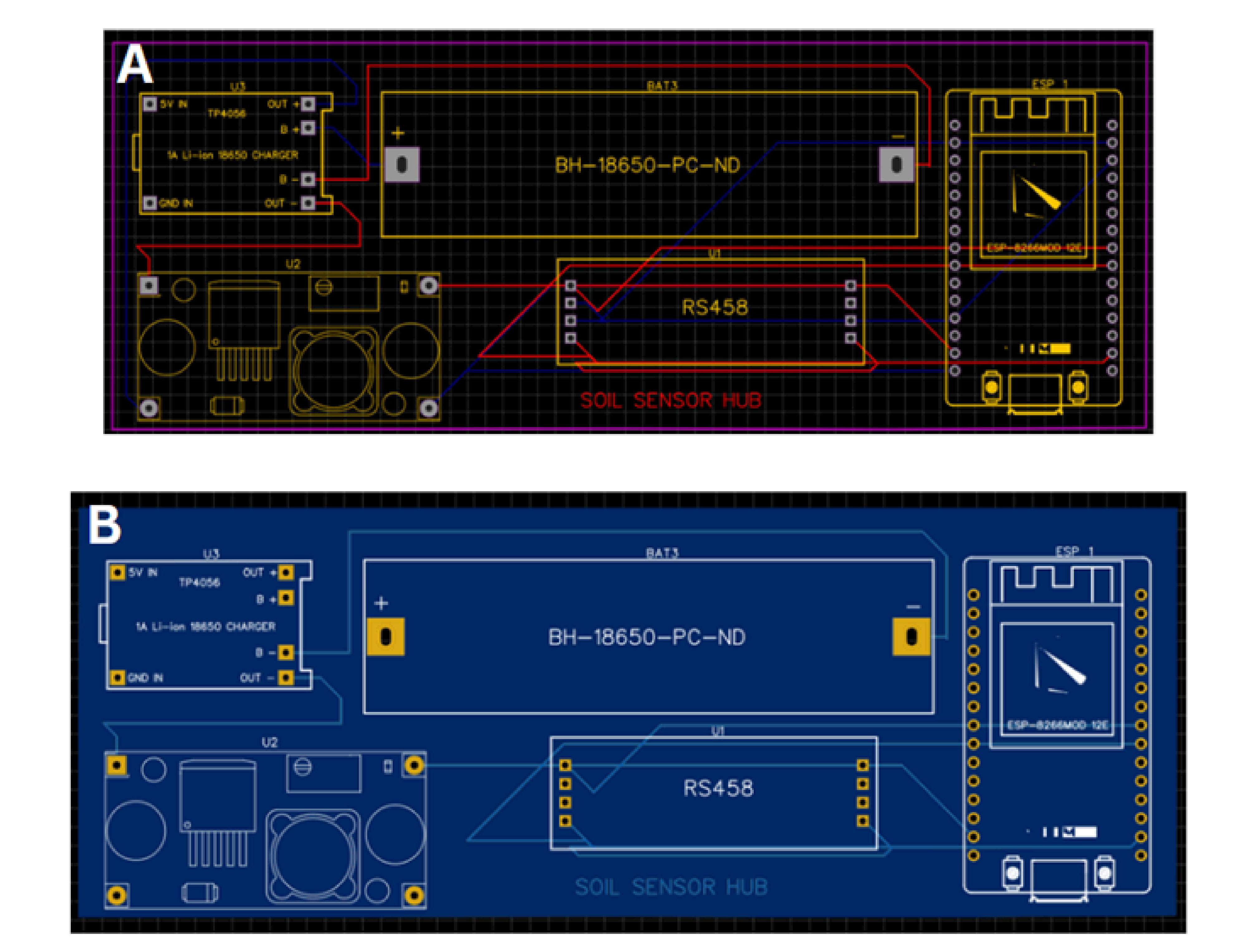
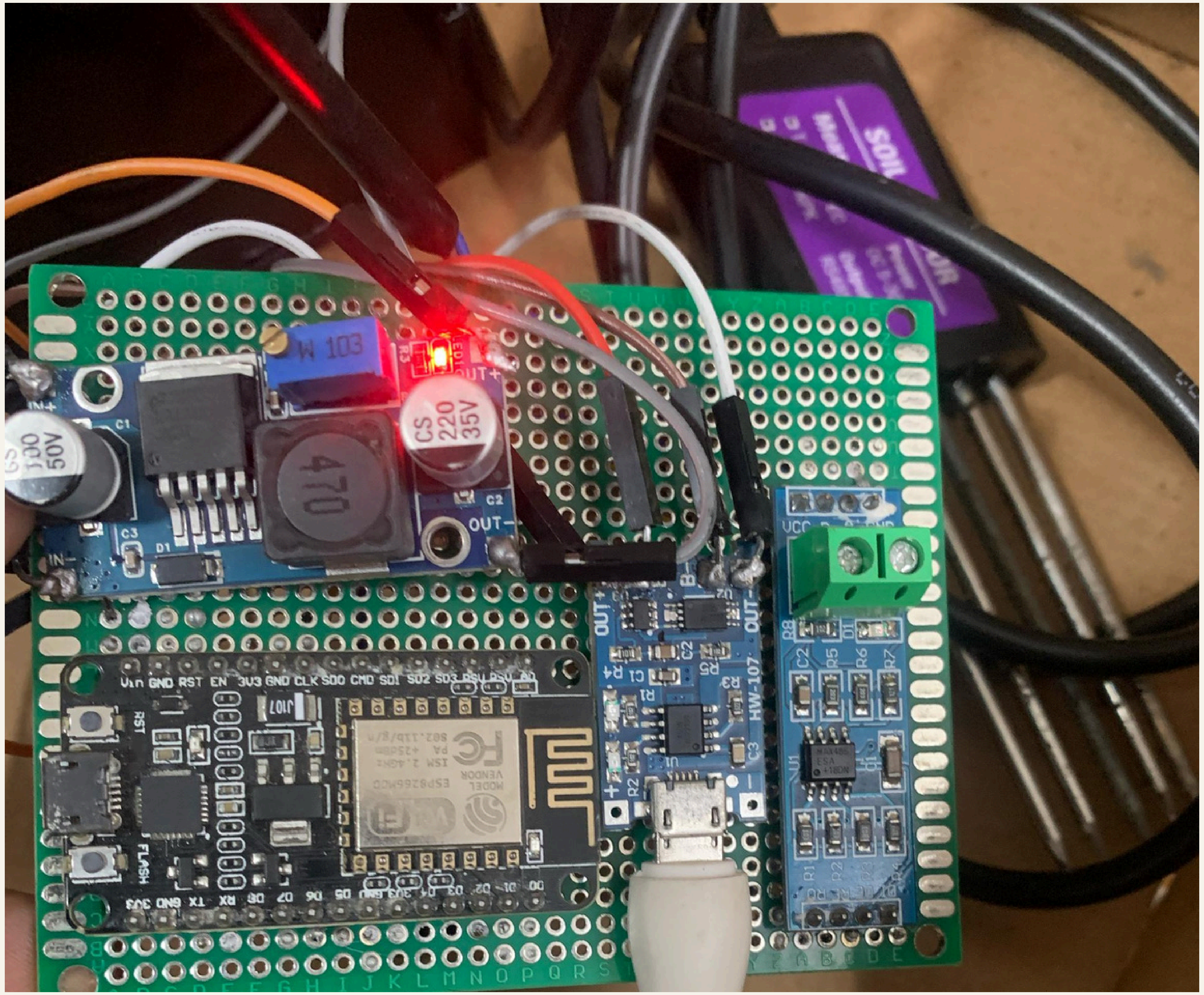


Image A shows the circuit tracks. Image B displays the 3D view of the manufactured PCB.

PERF-BOARD


W 103
CS 220 35V
470
OUT+
OUT-
IN+
IN-
Vin GND RST EN 3V3 GND CLK SD0 CMD SD1 SD2 SD3 RSV RSV A0
3V3 GND TX RX D8 D7 D6 D5 GND 3V3 D4 D3 D2 D1 D0
RST
FLASH
HW-107
VCC
SOIL

POWER CONSUMPTION

Active Mode Consumption for the Sensor Hub

Measured active current: 267.1 mA

Active time per hour: 10 seconds

Active energy per hour = 267.1mA x (10/3600) = 0.7419mAh

Deep Sleep Mode Consumption for the Sensor Hub

Measured deep sleep current: 7.1 μA

Deep sleep time per hour: 3590 seconds

Deep Sleep energy per hour = 7.1 μA x (3590/3600) = 0.00708mAh

Total energy consumption per hour = 0.7419 + 0.00708 = 0.74898mAh

AI FOR DISEASE DETECTION

SMART DATASET PREPARATION FOR MACHINE LEARNING IN CROP DISEASE DETECTION

- Automate Data Preparation
- Cleans the Data Automatically
- Reproducible and Consistent

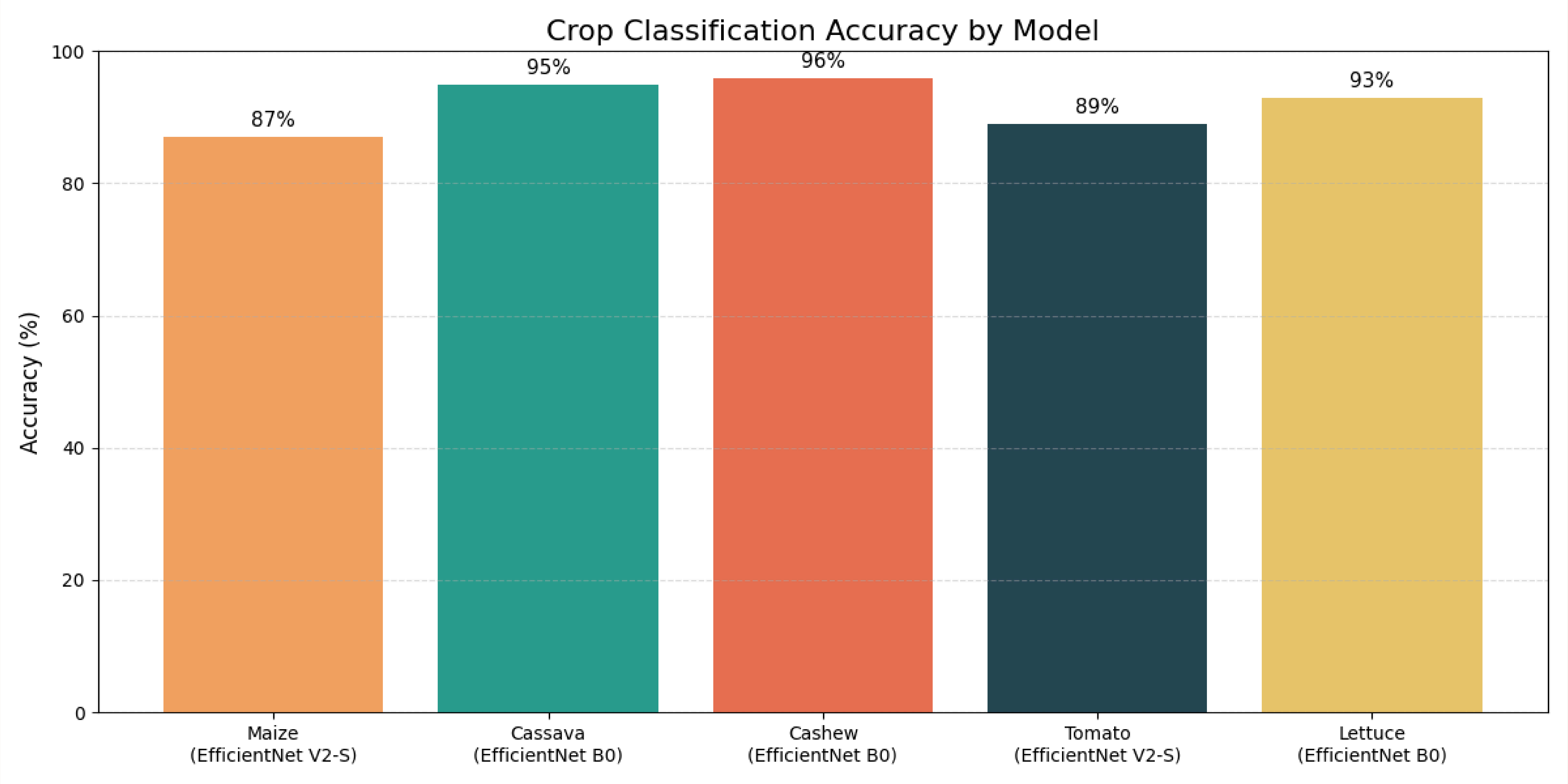
AUTOMATED DEEP LEARNING PIPELINE FOR CROP IMAGE CLASSIFICATION

- **End-to-End Pipeline**
  Fully automated image classification pipeline: preprocessing → training → evaluation → saving.
- **Dynamic Model Selection**
  Automatically chooses the best EfficientNet model (B0, B2, V2-S) based on dataset size.
- **Advanced Data Augmentation**
  Includes Mixup augmentation to improve generalization and reduce overfitting.
- **Robust to Noisy Data**
  Handles corrupt or truncated images gracefully with fallback strategies.
- **Custom Dataset Class**
  Modified PyTorch ImageFolder to improve resilience during training.

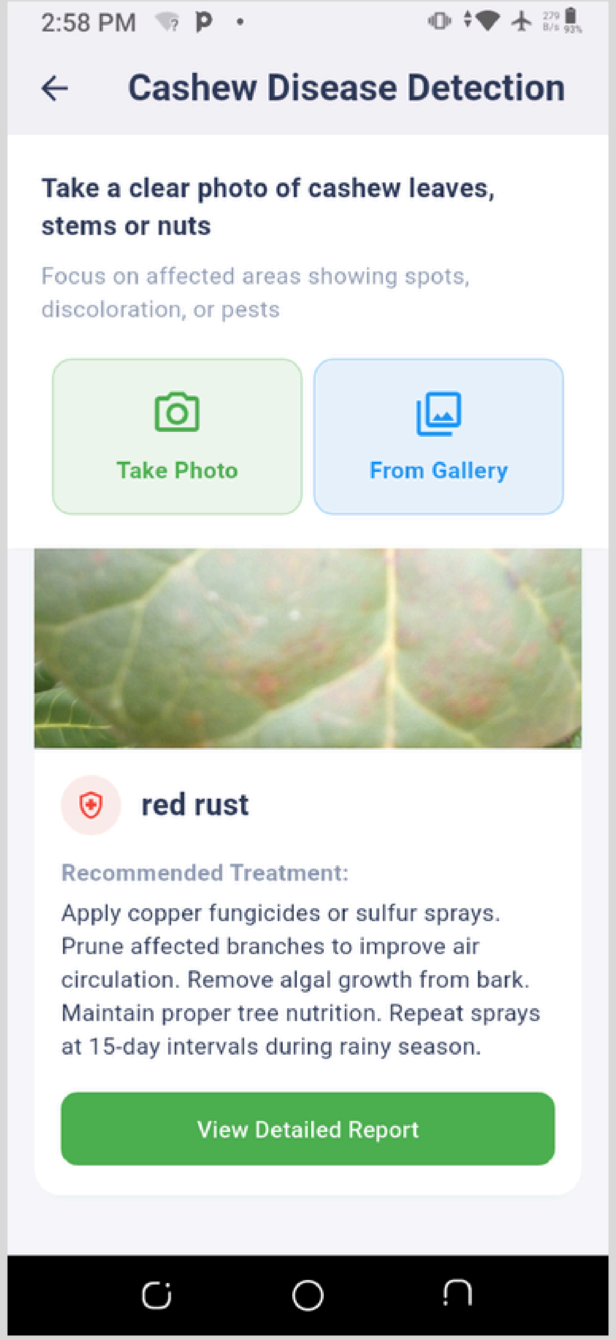
AUTOMATED DEEP LEARNING PIPELINE FOR CROP IMAGE CLASSIFICATION

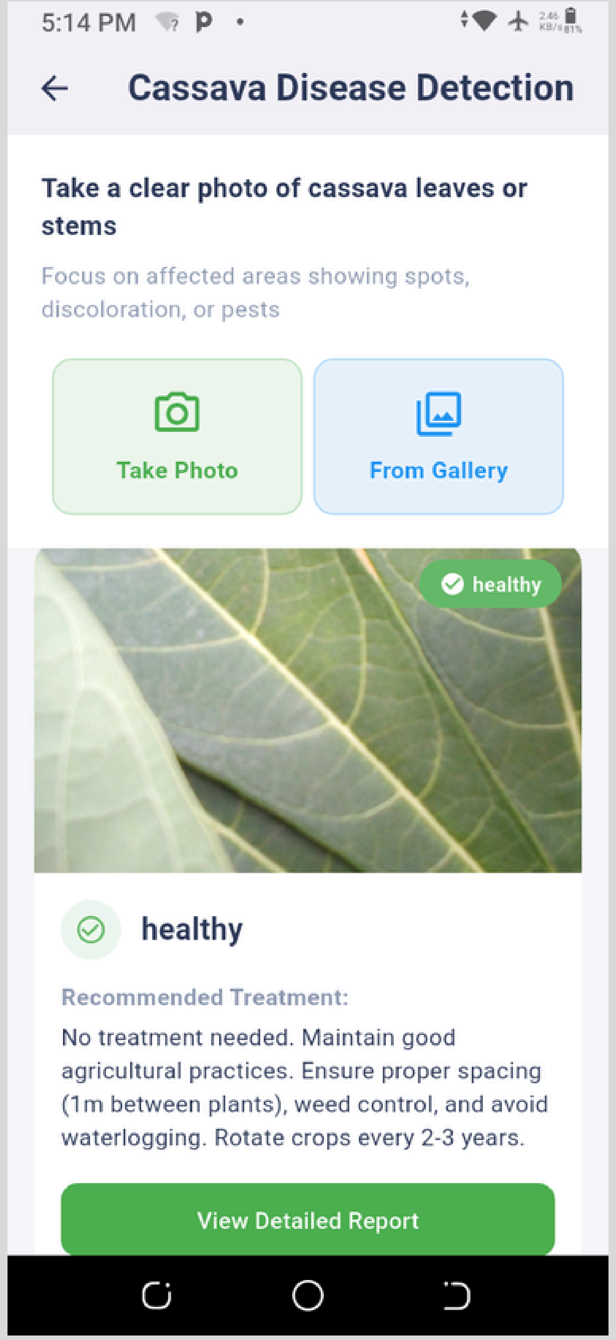
- **Training Best Practices**
  Implements early stopping, learning rate scheduling, weight decay, and seed setting.
- **Multi-Dataset Support**
  Trains separate models for multiple classes (e.g., crops) in one run.
- **Cloud Integration**
  Seamlessly works with Google Colab and Google Drive for cloud-based training and storage.
- **Progress Tracking & Visualization**
  Automatically saves training history, plots, model checkpoints, and per-class accuracy.
- **Modular, Scalable, and Reusable**
  Clean structure makes it easy to adapt, extend, and deploy in real-world projects.

TRAINING RESULTS



MACHINE LEARNING FOR DISEASE DETECTION MODEL IN ACTION



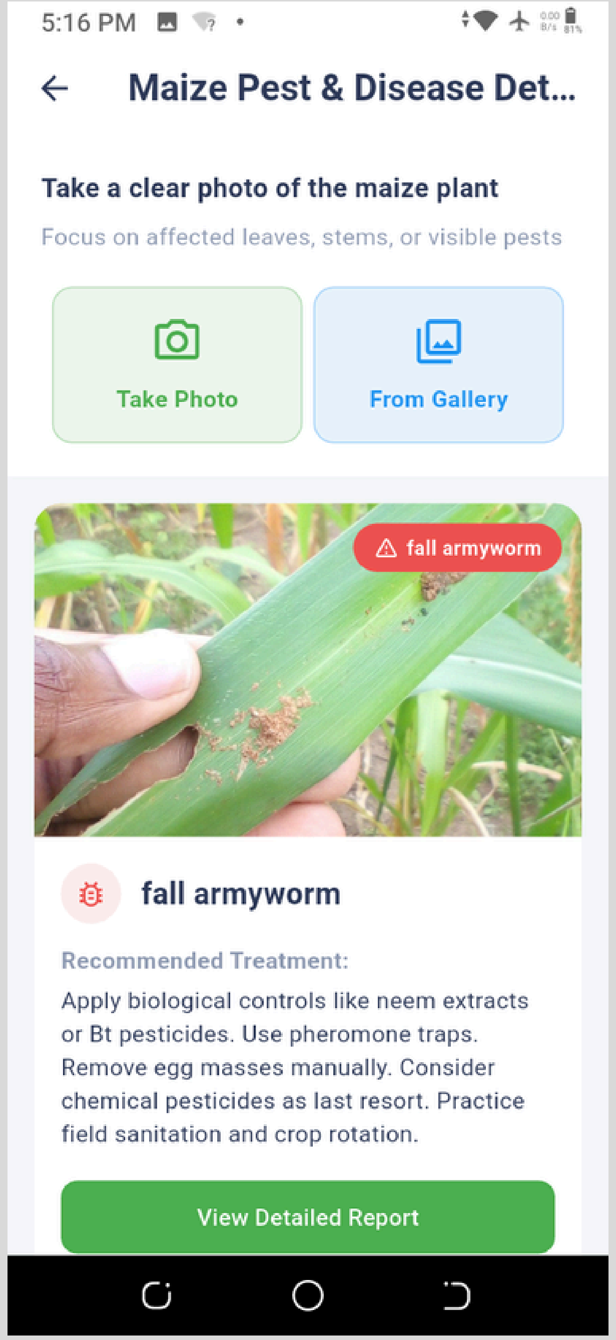


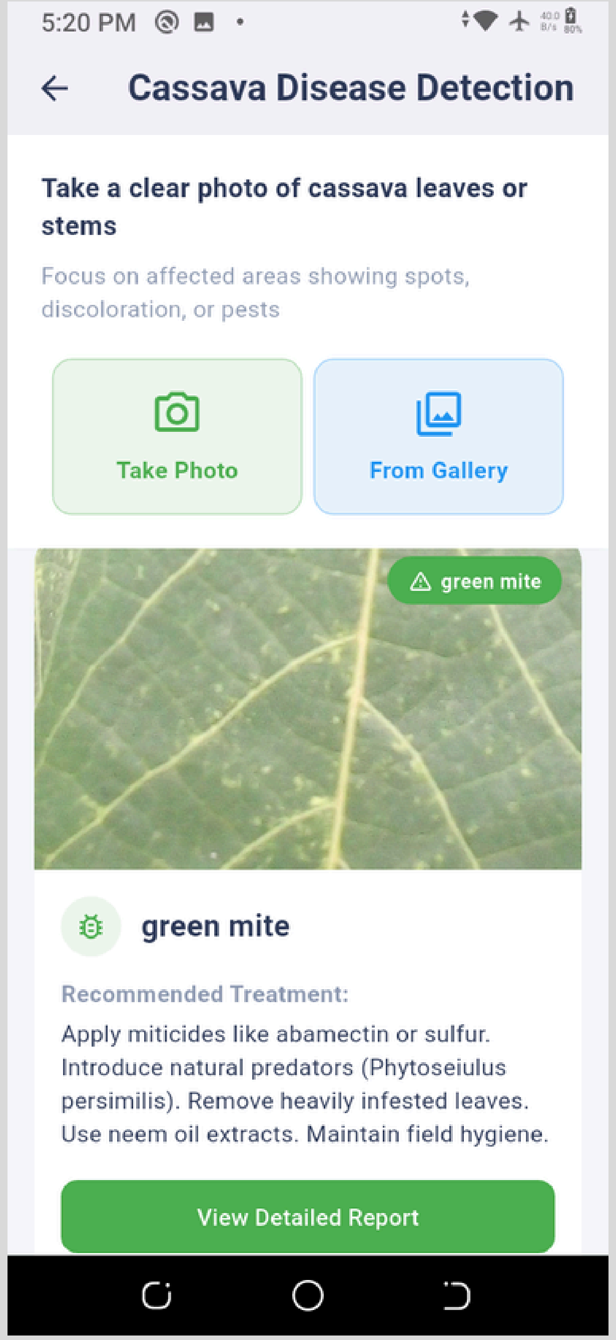
Red Rust in Cashew Detected Successfully

Healthy Cassava Detected Successfully

Average Inference time: 50 milliseconds

MACHINE LEARNING FOR DISEASE DETECTION MODEL IN ACTION



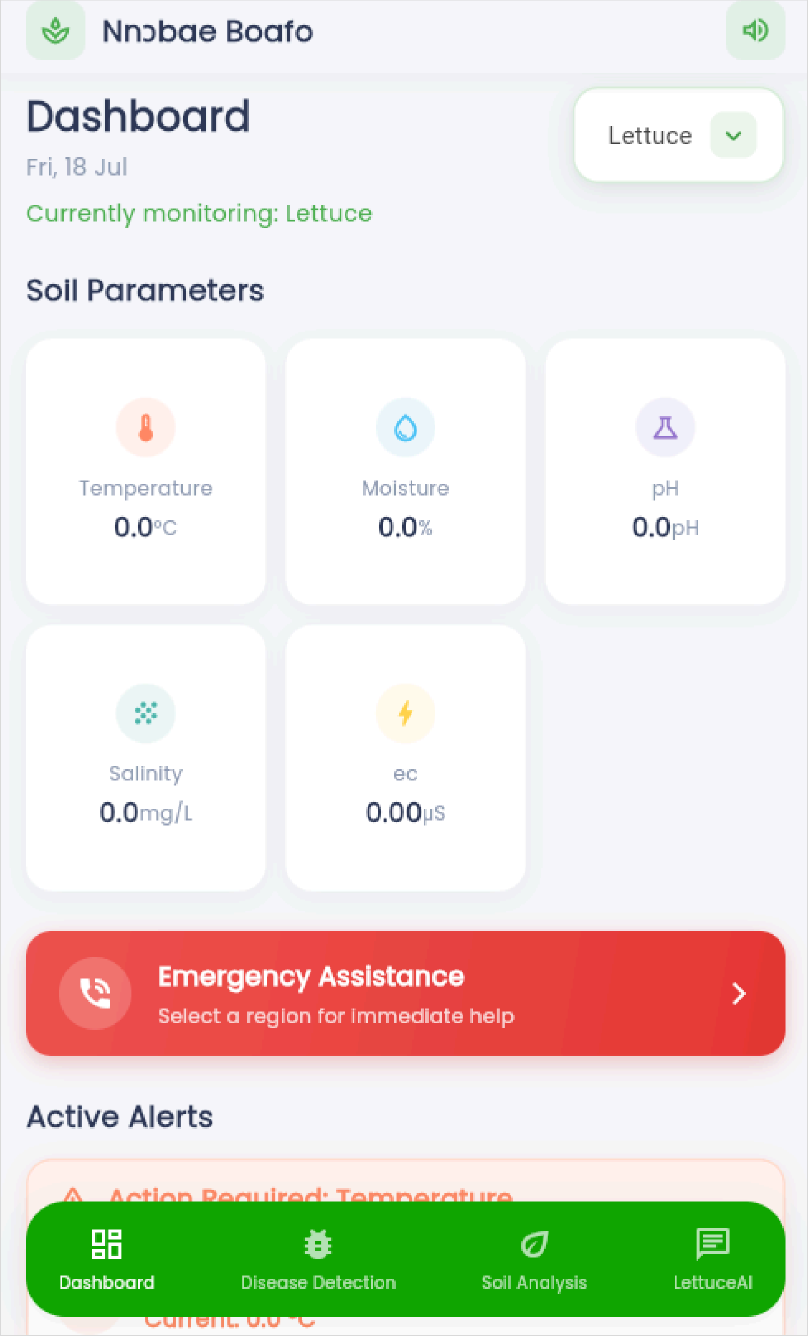


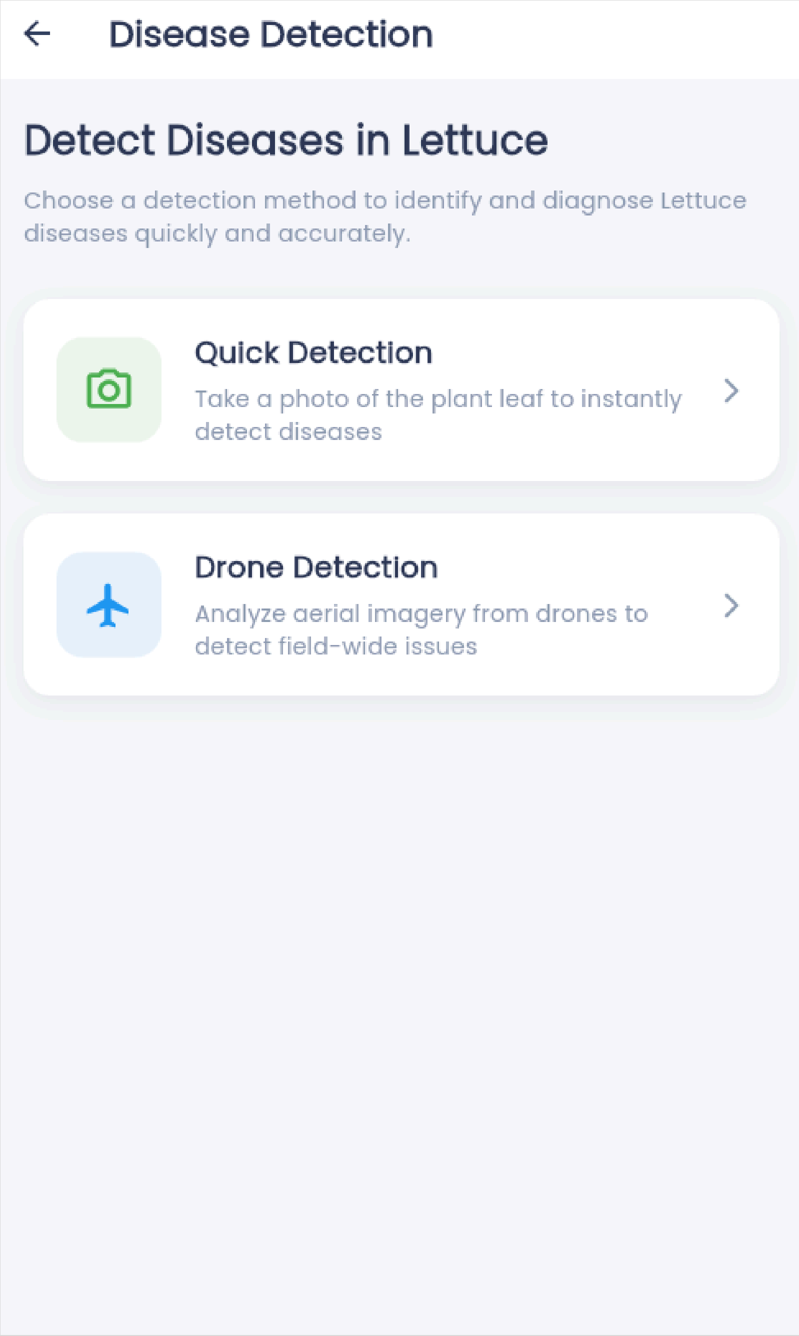
Fall army worm in Maize Detected Successfully

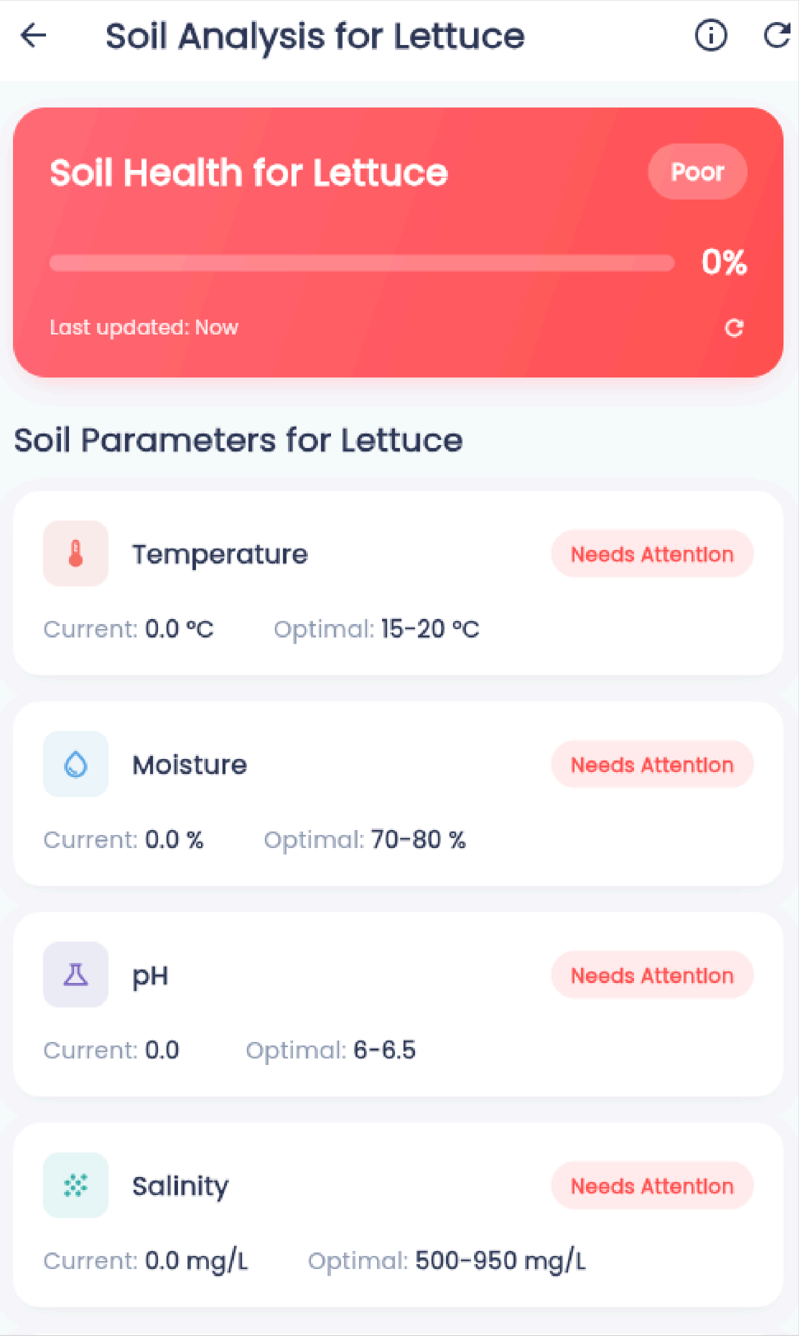
Green Mite in Cassava Detected Successfully

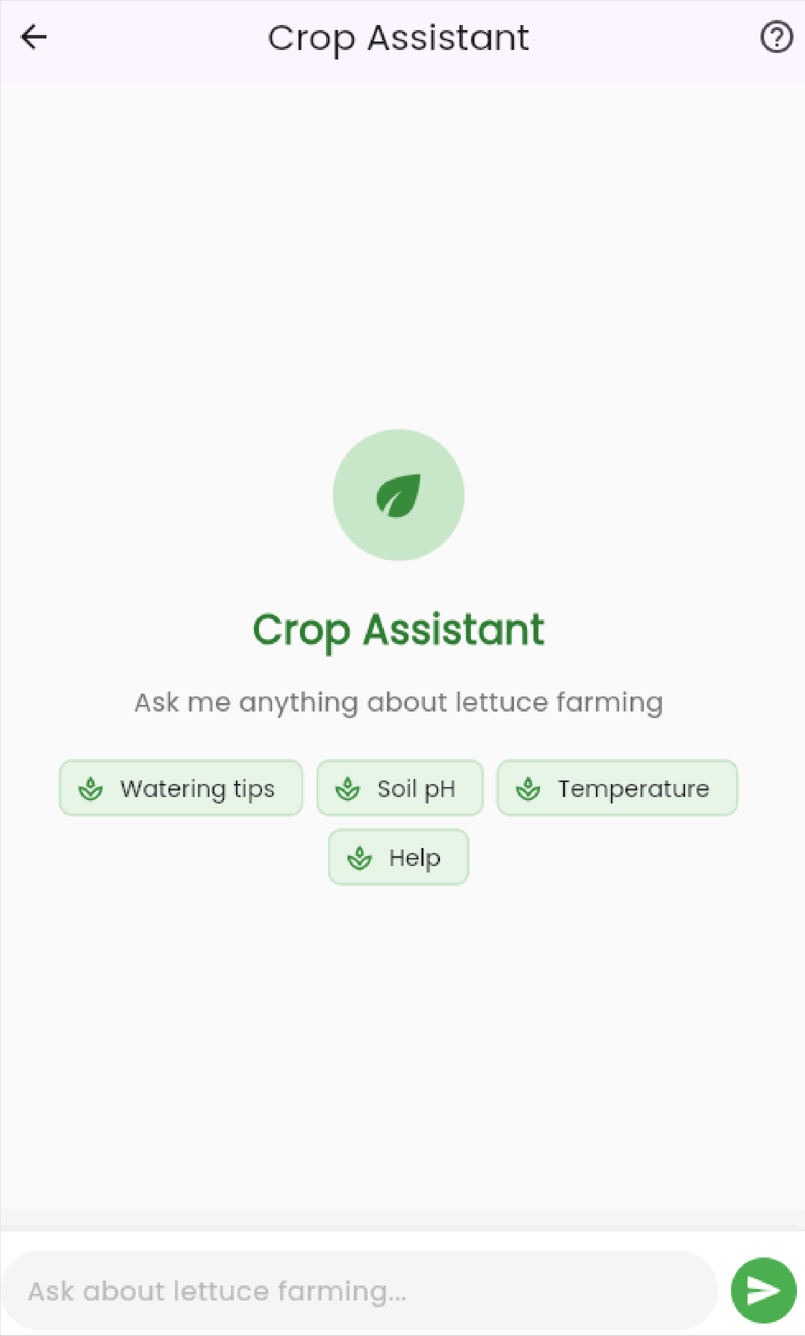
Average Inference time: 50 milliseconds

THE MOBILE APP – NNƆBAE BOAFO(FRONTEND)









Operates offline using WLAN Access Point

THE MOBILE APP FEATURES

- AI disease detection for crops (Cashew, Cassava, Maize, Tomato, Lettuce)
- View Soil parameters (Soil Temperature, moisture, pH, Salinity, and EC)
- View Soil Health
- Get assistance from an Agronomist by phone call
- Active Alert on Farm Status with recommendations
- Crop Assistant
- Text-to-Speech for visually impaired users

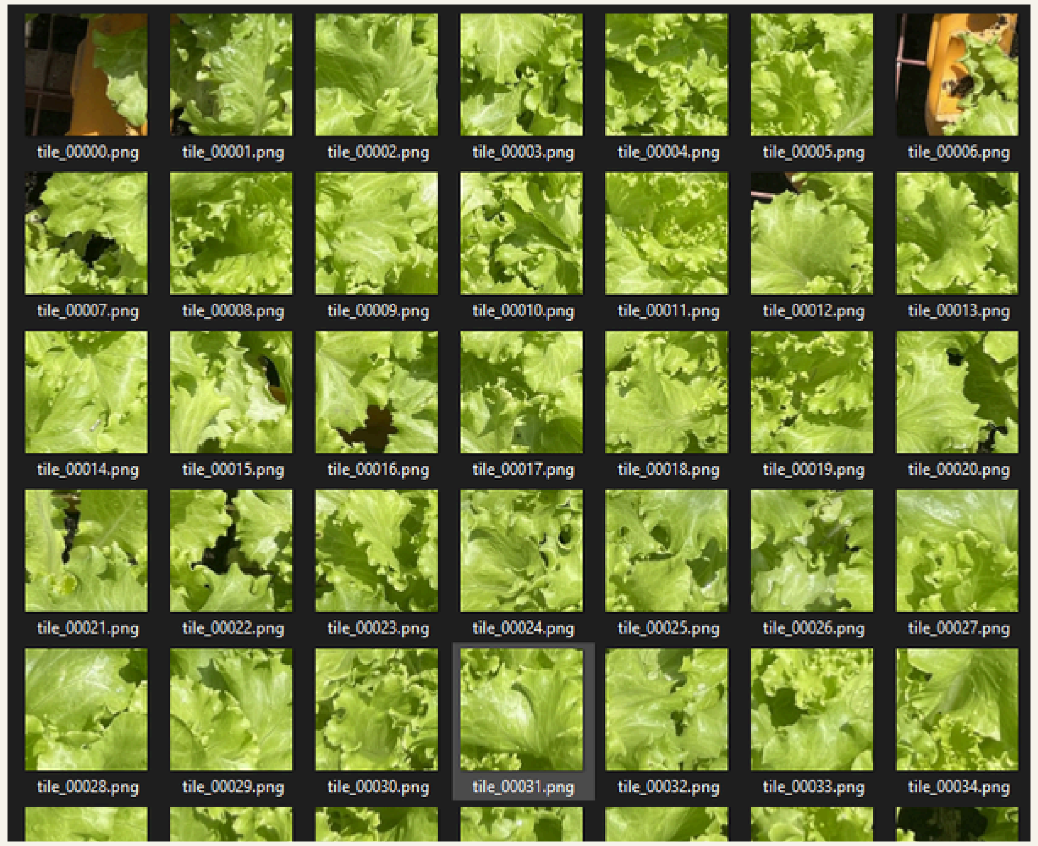
DRONE TECHNOLOGY - DJI MINI PRO 3

Why DJI MINI PRO 3?

- 4K 30 fps camera
- Flight time: 34 mins
- Better camera control
- Safety feature like obstacle avoidance
- Homebase

DRONE IMPLEMENTATION

- Capture: The Farmer captures an aerial view using the drone.
- Upload: Images transferred to WLAN infrastructure for processing
- Pre-process: Images tiled into smaller segments.
- Detection: Tiles are processed by the model.
- Output: number of infected crops + treatment suggestions



WHAT MAKES OUR WORK UNIQUE

1. Lightweight ML Model Optimized for Raspberry Pi for Disease Detection
   - The EfficientNet-B0,V2_S model was carefully selected, compressed, and optimized for low-resource hardware, enabling real-time disease detection without the cloud.
   - Competing solutions typically rely on cloud GPUs or heavy mobile processing.

2. Offline Functionality with Local Edge Processing
   - Unlike many solutions that require constant internet access, our system uses a Raspberry Pi server to process sensor and drone data offline.
   - Ensures full functionality in rural or remote farms with poor connectivity.

3. Full Soil Parameters
   - Soil Temperature, Soil Moisture, Soil ph, Soil Salinity, Soil Electrical Conductivity

WHAT MAKES OUR WORK UNIQUE

4. CropAI – Agriculture-Specific Conversational Assistant
    - Unlike generic dashboards, our mobile app includes a custom-trained AI chatbot that gives contextual responses tailored to each of the five crops we worked on.

5. Cost Effective
    - Prioritized affordable components and low-power sensors, making it viable for smallholder farmers in the country

LIMITATIONS & CHALLENGES

1. Scalability Constraints

While effective on small to medium-sized farms, large-scale deployments may demand enhanced network infrastructure, storage, and processing capabilities for real-time disease analysis.

2. Dataset Evolution Need

Emerging diseases or new crop variants will require continuous model updates and retraining to maintain detection relevance and accuracy.

FUTURE WORK

1. Drone Automation
    - Integrate GPS-based autonomous navigation for scheduled drone flights.
    - Enable fully automated aerial surveys without manual piloting.

2. Hardware Enhancements
    - Integrate a solar-powered module so the system can run continuously even where conventional electricity is unavailable.

3. Large-Scale Deployment & Testing
    - Pilot the system on a commercial farm to test network reliability and sensor distribution under scaled conditions.

REFERENCES

[1] United Nations, “World population projected to reach 9.8 billion in 2050, and 11.2 billion in 2100,” United Nations, 2024. https://www.un.org/en/desa/world-population-projected-reach-98-billion-2050-and-112-billion-2100

[2] “Gross domestic product and agriculture value added 2013–2022. Global and regional trends,” Statistics, Dec. 06, 2024. https://www.fao.org/statistics/highlights-archive/highlights-detail/gross-domestic-product-and-agriculture-value-added-2013-2022.-global-and-regional-trends/en

[3] “Africa: agriculture as share of GDP 2023 | Statista,” Statista, 2023. https://www.statista.com/statistics/1498552/agriculture-as-share-of-gdp-in-africa/

[4] L. Goodwin and B. Lipinski, “How Much Food Does the World Really Waste? What We Know — and What We Don't,” World Resources Institute, Nov. 25, 2024. https://www.wri.org/insights/how-much-food-does-the-world-waste

[5] WWF, “One-sixth of food produced is lost before it leaves the farm, WWF report finds,” www.wwf.eu, Jul. 21, 2021. https://www.wwf.eu/?4049841/fifteen-per-cent-of-food-is-lost-before-leaving-the-farm-WWF-report

REFERENCES

[6] Sekinat Durojaye, “The Economic Impact of Post-Harvest Losses in Sub-Saharan Africa - Sesi Technologies,” Sesi Technologies, Oct. 14, 2024. https://sesitechnologies.com/the-economic-impact-of-post-harvest-losses-in-sub-saharan-africa/

[7] T. White, “Figure of the week: Closing the gender gap to reduce food insecurity in Africa,” Brookings, May 26, 2021. https://www.brookings.edu/articles/figure-of-the-week-closing-the-gender-gap-to-reduce-food-insecurity-in-africa/

[8] M. Padhiary, D. Saha, R. Kumar, L. N. Sethi, and A. Kumar, “Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation,” Smart Agricultural Technology, vol. 8, p. 100483, Aug. 2024, doi: https://doi.org/10.1016/j.atech.2024.100483.

[9] Bongiovanni, R., & Lowenberg-DeBoer, J. (2004). Precision agriculture and sustainability. Precision Agriculture, 5(4), 359-387.

[10] Gebbers, R., & Adamchuk, V. I. (2010). Precision agriculture and food security. Science, 327(5967), 828-831.

Ghana AI Hackaton | 2025

THANK YOU