AgroVision: Crop Management Companion

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***Abstract*—This research presents an efficient solution to modern agricultural challenges by integrating machine learning and geospatial technologies for real-time crop monitoring. The proposed system leverages YOLO NAS (You Only Look Once – Neural Architecture Search), a high-performance object detection model known for its speed and accuracy in real-time applications. Trained on both public datasets (e.g., Kaggle) and real-world farm data, the model ensures robust detection across diverse agricultural environments.The system performs three key tasks: identifying crop ripeness for optimized harvesting, detecting early signs of plant disease for timely intervention, and distinguishing crops from weeds for targeted removal. These capabilities help improve yield quality, reduce manual labor, and support sustainable farming practices.To enhance decision-making, the system integrates Geographic Information System (GIS) software for spatial mapping of plant health data, enabling farmers to localize issues and allocate resources precisely. This research specifically focuses on strawberry cultivation and is implemented on a mobile rover equipped with a camera for field image capture and controlled remotely via the Blynk IoT platform.Designed to be cost-effective and scalable, the system offers a practical solution for small- to medium-scale strawberry farms, with potential for future expansion to other crops.**

***Index Terms*—Machine Learning, Precision Agriculture, YOLO NAS, Object Detection, Strawberry Crop Monitoring, Disease Detection, Ripeness Detection, Weed Identification, GIS Mapping, Smart Farming, IoT in Agriculture, ESP8266 Rover, Real-Time Crop Analysis, QGIS Visualization, Agricultural Automation**

I. Introduction

In recent years, the agricultural sector has increasingly embraced digital innovations to overcome long-standing challenges related to labor, efficiency, and sustainability. Much like how smartphones revolutionized communication, machine learning and computer vision technologies are now enabling smarter, data-driven decisions in farming. Precision agriculture, in particular, uses technology to monitor crop conditions, allocate resources more effectively, and boost productivity while minimizing waste.

This project introduces an automated system that tackles three critical aspects of crop management: identifying ripe fruits, detecting early signs of plant disease, and recognizing weeds for targeted removal. Traditionally, these tasks rely on visual inspection by farmers, which can be labor-intensive and inconsistent. AGROVISION automates this process by combining machine learning-based object detection with geospatial mapping, delivering precise insights in real time. Initially, this system is developed and tested on strawberry crops, which are particularly sensitive to ripeness and disease timing.

The system is composed of three main elements: a mobile rover to collect field-level imagery, a YOLO NAS model for high-speed, high-accuracy image analysis, and a GIS (Geographic Information System) interface to visualize the spatial distribution of crop conditions. The rover, built using a lightweight ESP8266 microcontroller, is remotely operated through the Blynk IoT platform and equipped with a camera to capture continuous video of crop rows.

Captured images are processed using YOLO NAS, a cutting-edge object detection algorithm optimized for speed and accuracy. Results are then visualized in QGIS, enabling farmers to view ripeness zones, disease clusters, and weed growth across their fields. This integration of machine learning and spatial technology offers a scalable solution to enhance crop monitoring, reduce manual labor, and promote sustainable agriculture.

A. Objective

- To automate the detection of ripe strawberries, plant diseases, and weeds using deep learning.
- To implement real-time object recognition through a YOLO NAS-based vision system.
- To integrate spatial analysis using GIS for mapping crop health and maturity across farm plots.
- To enable remote field monitoring via a mobile-controlled autonomous rover.

- To reduce manual labor and enhance decision-making with location-specific, data-driven insights.

B. Problem Statement

Traditional crop monitoring techniques rely heavily on manual inspection, which is time-consuming, inconsistent, and inefficient for large-scale farms. While some AI-based solutions exist, they often lack integration with real-time field data and fail to provide geospatial insights. AGROVISION addresses this gap by combining high-speed object detection, GIS-based mapping, and autonomous rover data collection to deliver a scalable, real-time crop monitoring and management solution.

II. Literature Review

Recent advancements in computer vision, particularly the YOLO (You Only Look Once) family of models, have significantly enhanced object detection capabilities in agricultural applications. These models have been instrumental in tasks such as fruit ripeness detection, weed identification, and disease phenotyping, contributing to the development of intelligent, real-time monitoring systems.

Strawberry Ripeness Detection: Nergiz (2023) evaluated YOLOv7 for strawberry detection, demonstrating its proficiency in accurately identifying ripe strawberries in complex environments, thereby optimizing manual harvesting operations. Similarly, He et al. (2023) proposed an enhanced YOLOv5s architecture tailored for real-time strawberry detection in open-field conditions, facilitating effective robotic harvesting under variable lighting and field scenarios. Li et al. (2023) introduced YOLOv5-ASFF, a multistage detection algorithm that incorporates adaptive spatial feature fusion, leading to improved accuracy in complex, multi-object environments. Further advancements include the YOLOv11-HRS model, which integrates hybrid attention mechanisms and specialized modules to enhance small-target detection and feature representation in challenging field conditions .

Weed Detection: Weed management is a critical aspect of precision agriculture. Studies have demonstrated the efficacy of YOLO-based models in real-time weed detection. For instance, an autonomous agricultural robot utilizing YOLOv8 and ByteTrack achieved high precision in identifying various weed species under diverse field conditions . Additionally, the GE-YOLO model, an enhancement over YOLOv8, was developed to improve weed detection accuracy in rice paddy fields by addressing limitations in feature extraction and fusion . Another study introduced the YOLOv8-MBM model, which incorporates a lightweight visual converter and multi-scale feature fusion to enhance weed detection in wheat fields .

Disease Phenotyping: Integrating disease detection into the same framework as ripeness monitoring can significantly aid farmers in making timely management decisions. Ilyas et al. (2021) focused on multi-scale context aggregation for strawberry fruit recognition and disease phenotyping using deep learning models, including YOLO architectures, demonstrating the potential for comprehensive crop monitoring. Moreover, the YOLO-Leaf model was proposed for detecting apple leaf diseases, utilizing advanced convolutional techniques and attention mechanisms to achieve high detection accuracy .

Integrated Approaches: While prior studies have primarily addressed ripeness detection, weed identification, or disease phenotyping in isolation, there is a growing trend towards integrating these functionalities into a unified system. For example, the WeedVision framework employs advanced object detection models to classify weeds at various growth stages, providing a comprehensive solution for weed management . Similarly, the WeedMap framework processes multispectral images using deep neural networks to create large-scale semantic weed maps, aiding in precision farming .

Current Research Focus: Building upon these advancements, the current research aims to develop an economical, rover-based system that integrates YOLO-based real-time detection of ripe strawberries, plant diseases, and weed presence. By combining YOLO's powerful object detection capabilities with geospatial mapping (GIS integration) and farmer-oriented application interfaces, the system seeks to provide actionable, location-specific insights. This holistic approach not only improves harvesting efficiency but also enhances disease management and weed control across dynamic field environments, offering a scalable solution for precision agriculture.

Recent advancements in plant pathology and integrated disease management have significantly improved the ability to identify and control common strawberry diseases, enhancing crop health and yield quality.

TABLE I
Common Strawberry Diseases

Disease	Description
Powdery Mildew	White powdery spots on leaves and fruits
Leaf Spot	Purple/red spots with gray or white centers
Gray Mold	Gray fuzzy mold on fruits and flowers
Angular Leaf Spot	Water-soaked spots turning reddish-brown
Anthracnose Fruit Rot	Dark sunken lesions on fruits
Tip Burn	Browning of leaf tips from calcium deficiency or stress

Powdery Mildew is widely recognized as a major fungal disease affecting strawberries, characterized by white powdery spots on leaves and fruits. Studies have shown that sulfur-based fungicides effectively control this disease, especially when applied early in the growing season (Agrios, 2005). Additionally, agronomic practices such as increasing plant spacing to improve airflow and removing infected plant parts have been proven to reduce disease spread and severity (Pritts and Handley, 1998).

Leaf Spot diseases, presenting as purple or red spots with gray or white centers on leaves, have been controlled successfully using copper-based fungicides. Avoiding overhead irrigation and removing infected foliage reduce the moisture environment that favors pathogen development (Fletcher et al., 2015). This integrated approach mitigates disease impact on plant vigor.

Gray Mold, caused by Botrytis cinerea, produces gray fuzzy mold on flowers and fruits under moist, cool conditions. Its management involves a combination of cultural and chemical methods such as improving air circulation, timely removal of infected fruits, and fungicide applications at bloom (Elad et al., 2016). Harvest timing is also critical to minimize infection risk.

Angular Leaf Spot, a bacterial disease causing water-soaked lesions that turn reddish-brown, is managed primarily by copper bactericides and cultural practices like avoiding overhead irrigation and removing infected plants to limit bacterial spread (Koike et al., 2009).

Anthracnose Fruit Rot, responsible for dark sunken lesions on strawberry fruits, is controlled by preventative fungicide programs and sanitation practices such as removing infected material. The use of plastic mulch also helps reduce soil splash and inoculum transfer (Schaad et al., 2001).

Tip Burn, a physiological disorder manifesting as browning leaf tips due to calcium deficiency or environmental stress, is managed by ensuring consistent watering, calcium supplementation, and reducing plant stress factors (White Broadley, 2003).

TABLE II
COMMON STRAWBERRY DISEASES AND SOLUTIONS

Disease	**Solution**
Powdery Mildew	Sulfur fungicides, increase spacing, remove infected parts
Leaf Spot	Copper fungicide, remove infected leaves, avoid overhead watering
Gray Mold	Improve airflow, remove infected fruits, use fungicide at bloom, harvest timely
Angular Leaf Spot	Copper bactericide, avoid overhead irrigation, remove infected plants
Anthracnose Fruit Rot	Preventative fungicides, remove infected material, plastic mulch
Tip Burn	Calcium, consistent watering, reduce salt, protect from stress

Current research emphasizes integrated disease management that combines chemical control with cultural practices and environmental adjustments to sustainably manage strawberry diseases. Early detection and intervention remain key to minimizing economic losses and improving fruit quality.

III. METHODOLOGY

A. Working Model

B. Rover System Description

The designed rover system integrates hardware and software components to enable autonomous farm monitoring and real-time video-based analysis. The key components used are described below.

C. L298N Motor Driver Module

The L298N dual H-bridge motor driver is employed to control the movement of the rover's DC motors. This module receives control signals from the microcontroller and supplies sufficient current and voltage to the motors, enabling forward, backward, and directional movement. The module's onboard heat sink ensures stable performance under continuous operation in field conditions.

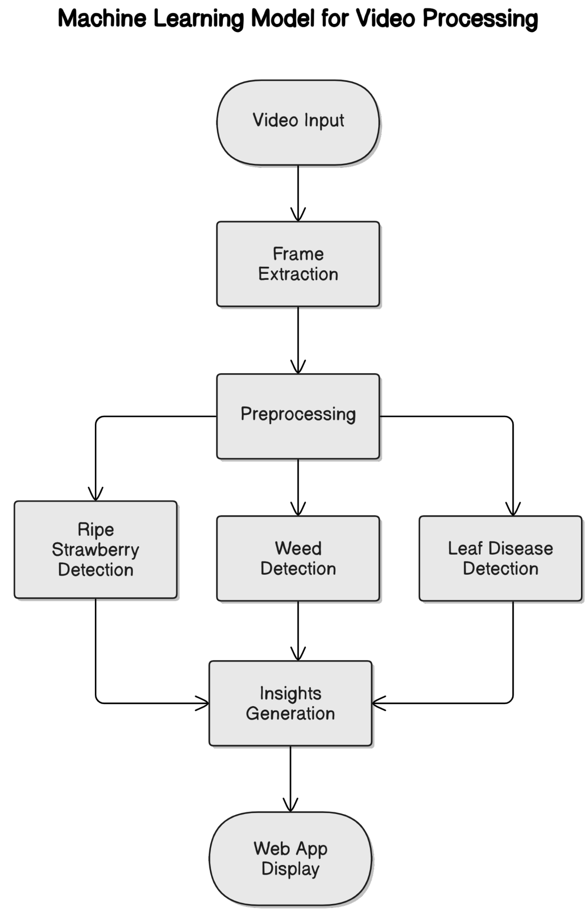


Fig. 1. Machine Learning Model for Video Processing

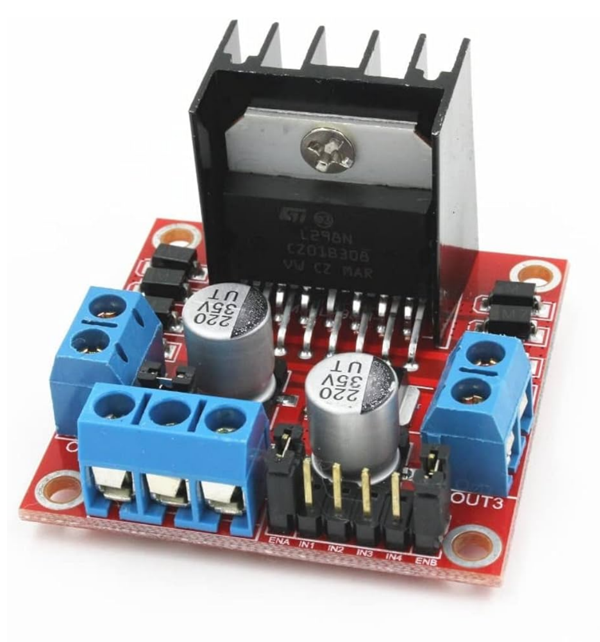


Fig. 2. L298N Motor Driver Module

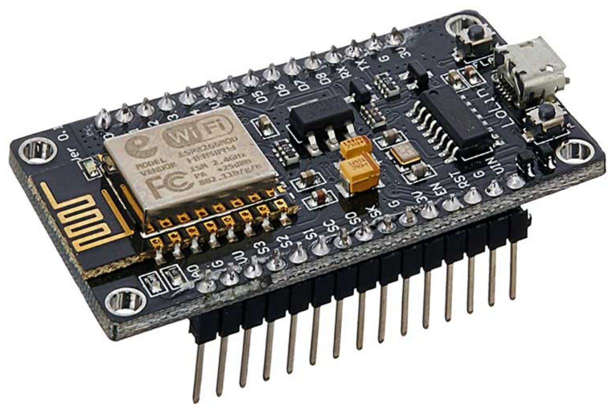


Fig. 3. NodeMCU ESP8266 Microcontroller

D. NodeMCU ESP8266 Microcontroller

The core control unit of the rover is the NodeMCU ESP8266, a Wi-Fi-enabled microcontroller. It handles the communication between the motor driver, the camera module, and the remote control system. The ESP8266's built-in Wi-Fi makes it suitable for IoT applications, allowing seamless connectivity between the rover and cloud-based services.

E. Blynk Platform for Remote Control

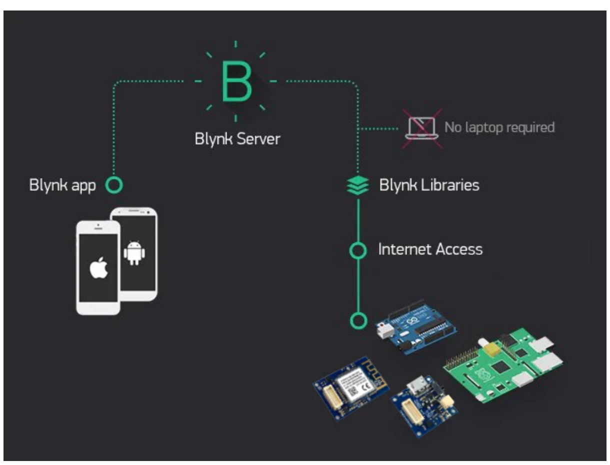


Fig. 4. Blynk Platform Architecture

The Blynk IoT platform is used to control the rover remotely via a mobile application. The Blynk app communicates with the Blynk server, which in turn interfaces with the ESP8266 using Blynk libraries over the internet. This setup eliminates the need for a local computer or laptop, enabling the farmer or operator to control the rover's movement and actions directly from a smartphone.

F. Camera Module

A lightweight camera module is mounted on the rover to capture live video streams of the field. The captured video is transmitted to the central processing unit, where individual frames are extracted and analyzed using the YOLO detection models for ripe crop, weed, and disease identification.

G. Workflow Summary

The rover navigates autonomously or under user control via the Blynk app, moving across the crop field while continuously capturing video. The camera feed is transmitted to the processing unit, where real-time frame extraction, preprocessing, and YOLO-based object detection are performed. The system identifies three critical categories: ripe strawberries ready for harvest, weeds requiring removal, and diseased leaves needing treatment. The detection insights are then packaged into actionable data and visualized through the farmer's web application, enabling timely interventions for crop management.

H. Video Capture

- The system begins by capturing real-time video data from the field using mobile cameras, drones, or stationary devices.
- This continuous video feed serves as the primary input for detecting ripe strawberries, weeds, and leaf diseases.

I. Frame Extraction

- Since deep learning models like YOLO process static images, the incoming video stream is divided into individual frames.
- This frame extraction step isolates meaningful still images at regular intervals, ensuring no critical information is missed.

J. Video Processing

- The captured video is processed frame by frame to extract plant images at regular intervals. Each frame is analyzed individually for detecting potential plant diseases.
- Preprocessing steps include resizing, normalizing, and enhancing frame quality to ensure accurate analysis in subsequent steps.

K. Detection Modules

- YOLO identifies ripe strawberries ready for harvest by analyzing color, shape, and texture features.
- Unwanted plants competing with crops are detected using YOLO's object classification capabilities.
- The system identifies leaves showing symptoms of common plant diseases (such as spots, discoloration, or wilting) for early intervention.

L. Geospatial Mapping

- Geographic Information System (GIS) technology is used to link the identified objects with specific locations on the farm.
- Each identified crop, disease, and weed is mapped with geospatial coordinates, allowing the farmer to visualize the spread of issues across the field.

M. Data Generation and Reporting

- A detailed report is generated containing:
- Identifying areas where crops are ready for harvest.
- Highlighting affected plants and severity of the disease based on detected symptoms.
- Pinpointing weed locations for targeted intervention.

N. Farmer Application Interface

- The farmer receives a mobile or desktop application interface that displays:
- Real-time Video Feedback, live updates showing detected crops, diseases, and weeds in the video feed.
- Geospatial Data, a map of the farm displaying the locations of ripe crops, diseases, and weeds, color-coded based on their status.
- Actionable Alerts, notifications with suggested actions, such as harvesting ripe crops, treating diseased plants, or removing weeds.

IV. Implementation and Result Analysis

The implementation phase of this project involved deploying a fully functional rover system equipped with camera modules and GPS sensors for autonomous data collection in strawberry farms. The rover navigates along predefined paths or via manual control, capturing high-quality images and videos of the crop environment. This collected data is stored on the rover and can be exported to a laptop system through USB or wireless transfer.

A. Data Processing and Software Architecture

Once the data is transferred, it is processed on a laptop using custom-built analysis software developed for this project. The software integrates a YOLO-based deep learning model trained for multi-task strawberry farm monitoring. Initially, image and video data are passed through the YOLO NAS inference pipeline, where three primary tasks are performed:

1) Ripe Strawberry Detection: The model successfully detects ripe strawberries in complex environments. Bounding boxes are drawn around the ripe fruits, and a **confidence score** is provided for each detection. The software aggregates the count of ripe fruits in each frame and across the video, giving the farmer an accurate estimation of harvest readiness. For instance, frames processed from video feeds show strawberries with confidence scores ranging from 51% to 65%, enabling even partially ripe fruits to be flagged for manual verification.

2) Disease Detection and Recommendations: The system identifies several types of common strawberry diseases with high accuracy, such as:

For each detected disease, the system outputs the affected part with a bounding box and assigns a **confidence score** (e.g., 80% to 90%). Importantly, the system provides **disease-specific agronomic recommendations** such as: These recommendations are dynamically displayed based on detection results, offering actionable insights without the need for expert intervention.

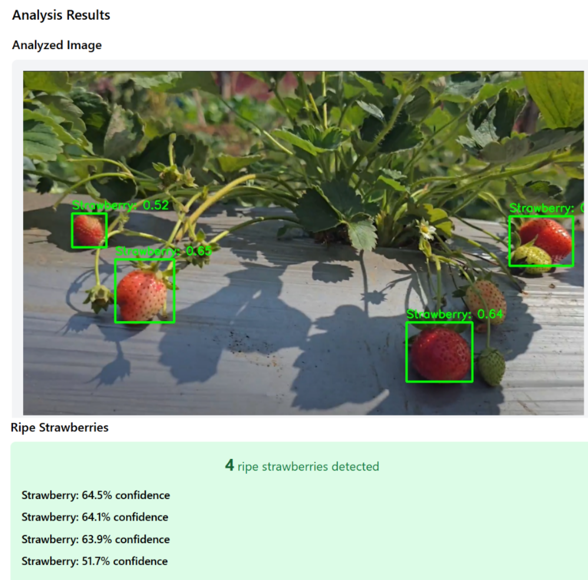
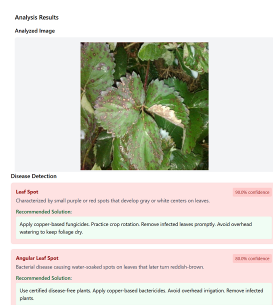
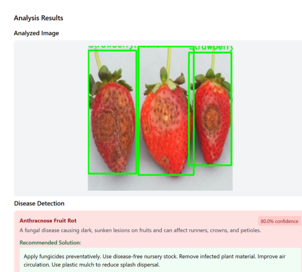


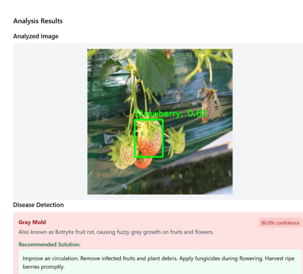
Fig. 5. Ripe strawberry detection



(a) Leaf Spot and Angular Leaf Spot



(b) Anthracnose Fruit Rot



(c) Gray Mold

Fig. 6. Diseases detection (a), (b) and (c)

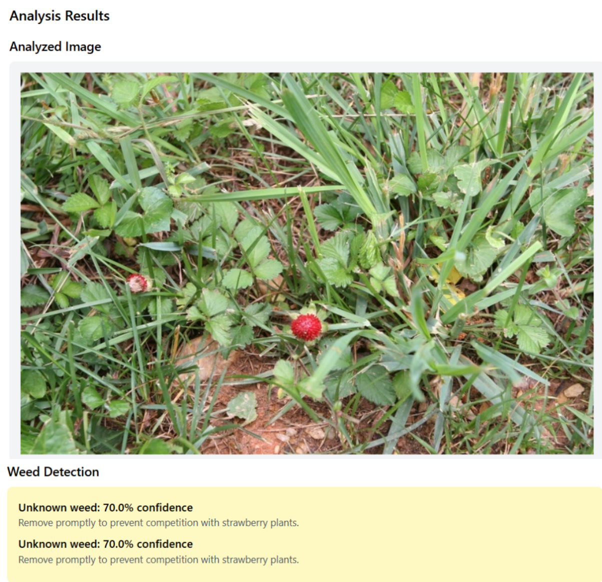


Fig. 7. Weeds detection

3) Weed Detection and Localization: Weed growth in the vicinity of strawberry plants is also detected. The system flags weed-covered zones and maps them with corresponding location data to help in precise weed management. Fig 7.

B. Video Analysis and Frame Extraction

The system is capable of analyzing continuous **video streams**. It intelligently extracts frames where ripe strawberries, diseases, or weeds are detected. Each extracted frame is timestamped and labeled, making it easier for farmers to review and track changes over time.

C. GIS-Based Location Mapping

A significant innovation in the system is the integration of **geospatial mapping (GIS)**. Each detection—whether ripe fruit, diseased leaf, or weed—is associated with a **GPS location pin**. This spatial tagging allows the software to generate visual field maps highlighting:

- Harvest-ready zones
- Disease hotspots
- Weed-infested areas

Such detailed geospatial insights enable the farmer to perform **targeted interventions**, reducing unnecessary labor and maximizing input efficiency.

D. User Interface and Farmer Interaction

The software is designed with a **user-friendly interface** where farmers can:

- View annotated images and videos
- Access disease-specific advice
- Monitor crop health trends over time
- Export reports with images, coordinates, and analysis results

This makes it accessible even to non-technical users, enhancing the real-world applicability of the system.

E. Performance and Results

In practical field tests, the model demonstrated robust performance in varying lighting conditions and foliage density. The detection pipeline runs efficiently on modest computing hardware, making it scalable for broader deployment. The system has shown potential to significantly:

- Improve harvest timing through accurate ripeness analysis
- Reduce crop losses by early disease identification
- Streamline farm management via location-specific reporting

TABLE III
SUMMARY OF DETECTION RESULTS

Type	Confidence Range
Ripe Strawberries	51.7% – 64.5%
Diseased Plants	80% – 90%
Weeds	60% – 75%

V. CONCLUSION

The integration of a rover-based data collection system with advanced image and video analysis has demonstrated a significant advancement in precision agriculture for strawberry farming. By automating the detection of ripe strawberries, plant diseases, and weeds—and providing geotagged insights along with confidence scores—our system empowers farmers to make informed, location-specific decisions. The ability to process both image and video inputs ensures adaptability in dynamic field conditions. Additionally, the software not only detects problems but also suggests suitable remedies, further assisting farmers in efficient crop management.

This approach minimizes manual effort, enhances crop yield quality, and streamlines resource allocation. The use of GPS mapping to pinpoint issues adds another layer of actionable intelligence, allowing for targeted interventions.

In the future, we plan to extend this system to support a wider range of crops beyond strawberries. By retraining the models and refining the detection algorithms, the same rover and software pipeline can be adapted to other fruit-bearing and vegetable crops, making it a scalable solution for diverse agricultural environments. Furthermore, integrating real-time, on-device processing using embedded systems will enhance field autonomy, reduce data transfer latency, and allow immediate feedback to farmers. This expansion aims to make smart farming accessible and effective for a broad spectrum of crop types and field conditions.

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