

AI-Driven Autonomous Robot for Crop Monitoring and Precision Farming

Prof. Dr. Aniruddha S. Rumale¹, Dr. Sushma Zade², Vedant Sonawane³,
Kaustubh Rahane⁴, Shraddha Dalvi⁵

Department of Information Technology¹⁻⁵

Sandip Institute of Technology and Research Centre (SITRC), Nashik, India

aniruddha.rumale@sitrc.org, vedantsonawane93@gmail.com,

kaustubhrahane1301@gmail.com, shraddhadalvi2710@gmail.com

Abstract: Agriculture plays an important role in food production and economic growth. However, crop diseases, improper soil moisture, and changing weather conditions can negatively affect crop health and reduce agricultural productivity. In many farming practices, farmers monitor crops through manual inspection, which is time-consuming and can delay disease detection. To address these challenges, this research proposes a low-cost, ground-based agricultural robot that combines deep learning with environmental monitoring to support precision farming.

The proposed system uses an existing YOLOv8-based model for crop disease detection, trained and evaluated using the PlantVillage dataset. The model achieved a reported test accuracy of 99.76% on the current test set. However, this result is based on testing on the dataset, and further evaluation is needed to assess performance under real-world field conditions. A four-wheel mobile robot equipped with a camera is planned to capture plant images at close range, while a laptop will process the images and predict possible crop diseases. An ESP32-based sensor module will also be integrated to monitor soil moisture, air temperature, relative humidity, rainfall, and water-tank levels. The collected sensor readings and disease detection results will be displayed on a dashboard, which will provide basic recommendations using predefined rules.

At present, the machine-learning model has been developed and tested using plant images. The construction of the robot, integration of sensors and dashboard, and testing in real agricultural environments are planned as the next stages of development. The proposed system aims to offer an affordable and modular solution for crop monitoring, early disease identification, and agricultural decision-making.

Keywords: Agricultural robot, YOLOv8, crop disease detection, PlantVillage dataset, precision agriculture, ESP32, environmental monitoring, machine learning

I. INTRODUCTION

Agriculture is essential for food production, employment, and economic development. However, crop growth and productivity can be affected by plant diseases, insufficient water, unsuitable soil conditions, and changes in the weather. Identifying diseases early and monitoring environmental conditions can help farmers take appropriate action and reduce potential crop losses.

Farmers usually monitor crop health by inspecting plants manually. Although this method is useful, checking large fields can take considerable time and requires knowledge of plant diseases. Some disease symptoms may be difficult to recognise during the early stages, which can delay treatment. Artificial intelligence (AI) and computer vision offer a way to support this process by analysing plant images and identifying signs of disease.

Deep-learning models can learn visual patterns from plant images and use them to identify specific disease categories. This project uses an existing YOLOv8-based model for crop-disease prediction. However, a model that performs well



on test images may not achieve the same results in an agricultural field. Differences in lighting, background, camera distance, and plant appearance can affect its predictions. Therefore, testing the model with images captured under actual farming conditions will be important for evaluating its practical performance.

To support crop inspection, this project proposes a four-wheel, ground-based agricultural robot fitted with a camera. The robot will be moved manually through the field to capture images of plants at close range. These images will then be processed on a laptop using the existing YOLOv8-based model, which will predict a disease category supported by the model. The robot is designed for ground-level inspection rather than aerial monitoring. This approach avoids the need for drone-related flight-control equipment and allows the team to focus on close-range image collection. Processing images on a laptop also avoids the immediate need for a dedicated onboard computing device.

In addition to image-based disease detection, the proposed system will monitor selected environmental conditions using sensors connected to an ESP32 microcontroller. The sensors will measure soil moisture, air temperature, relative humidity, rain presence, and water-tank level. The readings will be sent to a dashboard, where users can view the environmental measurements alongside the disease-prediction results. The dashboard will use predefined rules to generate simple alerts. For example, it may display a low-soil-moisture warning when the sensor reading falls below a specified threshold. Similarly, it may notify the user when the model identifies a supported crop disease. These alerts will help users decide when further inspection or action may be needed, but they will not replace professional agricultural advice.

The main objective of this project is to develop a low-cost agricultural prototype that combines crop-disease prediction, close-range image capture, and environmental monitoring in one system. The initial version will use manual robot control, allowing the team to evaluate image capture, sensor readings, and communication between the components. Future development may include autonomous navigation, which could allow the robot to move through fields with less human intervention and cover larger areas more efficiently.

II. RELATED WORK

Research on AI-based crop monitoring and precision agriculture can be grouped into four closely related areas: deep learning-based plant disease detection, vision-based agricultural robots, environmental monitoring using sensors, and integrated decision-support systems. Previous studies have demonstrated the potential of computer vision and machine learning for identifying crop diseases. However, practical agricultural deployment also depends on image quality, environmental variation, hardware cost, and the integration of model predictions with useful field information. The following subsections review relevant work in these areas and identify the research gap addressed by the proposed agricultural robot.

A. Deep Learning-Based Plant Disease Detection

Deep learning has become an important technique for identifying plant diseases from leaf images. Mohanty et al. [1] investigated convolutional neural networks (CNNs) for image-based plant disease detection using 54,306 images from the PlantVillage dataset. Their best-performing model achieved approximately 99.35% accuracy under the dataset evaluation conditions. However, performance decreased substantially when the model was evaluated on images obtained from different sources, highlighting the difficulty of applying models trained on controlled images directly to real agricultural environments.

Kamilaris and Prenafeta-Boldú [2] reviewed the application of deep learning in agriculture and discussed its use in tasks such as crop classification, disease detection, weed identification, and agricultural monitoring. Their review demonstrated the growing role of deep learning in precision agriculture while highlighting practical challenges related to datasets, computational requirements, and real-world implementation.

Recent work has also explored improvements to object-detection models for crop disease identification. YOLO-based approaches are useful for applications requiring rapid visual analysis and, where the model and dataset support it, localization of visible disease symptoms. Nevertheless, a high score on a curated dataset does not automatically



establish equivalent performance under changing field illumination, different camera distances, leaf occlusion, and natural backgrounds.

The proposed project uses YOLOv8 for plant image analysis. The model has achieved a reported test accuracy of 99.76% on the project's available test dataset. This result is specific to the current experimental dataset and should not be interpreted as confirmed field accuracy. Additional testing using images captured by the ground-based robot under real agricultural conditions is required.

B. Vision-Based Agricultural Robots

Agricultural robots provide a mobile platform for collecting crop images and supporting field-level monitoring. Unlike aerial platforms, ground-based robots can operate close to plants and capture images of individual leaves or plant regions. Their practical usefulness depends on factors such as chassis stability, camera placement, movement through crop rows, battery capacity, and the ability to process or transmit collected data.

Research has demonstrated the integration of mobile robots, RGB cameras, and deep learning for agricultural disease monitoring. A 2024 IEEE conference study described an IoT-integrated tomato plant disease detection system using an autonomous mobile robot, an RGB camera, sensors, and YOLOv8-based image analysis [3]. This work shows that combining a mobile platform with visual disease detection is an established research direction rather than a completely new concept.

Other agricultural robotics research has examined computer vision for crop monitoring, weed identification, and precision-farming tasks. However, system performance depends on the conditions in which the robot is evaluated, including crop arrangement, lighting, terrain, and the availability of representative training images.

The proposed project adopts a ground-based four-wheel rover as a practical platform for crop image acquisition. A laptop is intended to perform YOLOv8 inference, allowing the initial prototype to use existing computing resources instead of requiring a dedicated high-performance onboard computer. The robot's movement, camera-based acquisition, and AI analysis must be evaluated as an integrated system before real-time field operation can be claimed.

C. Environmental Monitoring and Sensor-Based Agriculture

Crop health is influenced by several environmental factors, including soil moisture, temperature, humidity, and rainfall. Visual analysis can identify patterns resembling disease symptoms, but an image alone may not provide sufficient information about the environmental conditions surrounding a plant. Environmental sensors can therefore complement image-based monitoring by providing additional measurements for interpretation and farm management.

Internet of Things (IoT)-based agricultural systems commonly use microcontrollers and connected sensors to collect environmental readings and make the information available through monitoring interfaces. Deep learning and computer-vision reviews also identify multimodal monitoring and practical deployment as important directions for precision agriculture [2], [4]. However, sensor readings must be interpreted according to crop requirements and local conditions; a single measurement should not be treated as definitive evidence of a particular disease or its cause.

In the proposed system, an ESP32-based sensor module is planned to collect soil moisture, temperature, humidity, and rain-presence information. These readings are intended to be presented alongside the crop image analysis. A rule-based decision-support component can then generate preliminary recommendations, such as checking irrigation requirements when the soil moisture reading is below a selected threshold.

This approach is intended to connect visual crop observations with environmental context in one monitoring workflow. The effectiveness of the integration will depend on sensor calibration, appropriate thresholds, reliable communication, and validation under representative agricultural conditions.

D. Integrated Monitoring and Decision Support

A crop-monitoring system becomes more useful when it presents its results in a form that farmers or operators can interpret. A dashboard can combine disease predictions, model confidence, environmental readings, timestamps, and



historical observations. Such a system can help users review findings and decide which plants or areas require further inspection.

Existing research demonstrates the potential of combining artificial intelligence, sensing, and connected monitoring for precision agriculture. Nevertheless, disease detection, environmental measurement, and decision support are often evaluated as separate technical components. A high-performing vision model alone does not establish that the complete agricultural monitoring system is reliable or useful in field conditions.

The proposed project is designed to bring these components together through a common dashboard. The intended interface will display YOLOv8 predictions and, following hardware integration, sensor measurements and time-stamped scan records. A confidence-aware mechanism may also be used to flag uncertain predictions for image recapture or manual verification. Recommendations will be generated using explicit rules and will be presented as preliminary guidance rather than as confirmed agricultural diagnoses.

E. Research Gap

The reviewed literature establishes that deep learning-based disease detection, mobile agricultural robots, and sensor-based crop monitoring are all active research areas. Mohanty et al. [1] demonstrated strong disease-classification performance on a controlled image dataset while also showing the limitations of generalization to images from other sources. The mobile robotic system reported in [3] illustrates that YOLOv8-based disease detection on a ground platform has already been investigated. Therefore, the use of a ground robot or YOLOv8 alone cannot be considered the principal novelty of the proposed project.

The practical challenge addressed by this project is the development and evaluation of an affordable, modular prototype that combines crop image analysis, environmental measurements, uncertainty handling, and historical monitoring in one workflow. The design separates the rover and camera, laptop-based inference, and microcontroller-based sensing so that the components can be developed and tested individually before full integration.

The intended contribution is the implementation of this combined workflow using accessible hardware and an existing trained model. The project will be evaluated through model testing, sensor validation, system-integration tests, and field-image experiments when these become available. A comparison with related systems and experimental results will be required to establish the practical advantages and any specific novelty of the final implementation.

No.	Identified research gap	Proposed solution	Evaluation method
[1]	High test accuracy may not reflect real-field performance.	Evaluate the model using independently captured crop images.	Compare dataset and field-image metrics.
[2]	Predictions may be affected by lighting and background changes.	Test the same model under different image conditions.	Record precision, recall and F1-score by condition.
[3]	Users may treat uncertain predictions as confirmed diagnoses.	Introduce a configurable confidence threshold.	Test correct handling of low-confidence predictions.
[4]	A disease label alone gives limited environmental context.	Display sensor measurements alongside predictions.	Verify that the correct readings appear with each scan.
[5]	Sensor values can be misinterpreted without calibration.	Calibrate sensors and document measurement limitations.	Compare readings against suitable reference measurements.
[6]	Environmental readings alone cannot establish the cause of a disease.	Generate cautious, rule-based recommendations with explanations.	Test defined sensor and prediction scenarios.
[7]	Individual modules may work separately but fail when	Connect the rover, camera, inference software and sensor	Perform end-to-end integration tests.



	integrated.	controller.	
[8]	Inference time may limit practical monitoring speed.	Measure processing time on the available laptop.	Report average inference time and images processed per second.
[9]	Historical observations may not be easy to compare.	Save timestamped scans and sensor readings.	Confirm storage, retrieval and comparison of records.
[10]	Repeated scans may be affected by changes in camera distance and angle.	Use a consistent image-capture procedure.	Compare repeat scans under controlled capture conditions.
[11]	Small-scale prototypes may have unclear hardware costs.	Prepare a bill of materials with component costs.	Report actual prototype cost and exclusions.
[12]	Dataset results may be difficult to reproduce.	Document dataset source, class labels, split, model configuration and evaluation metrics.	Re-run evaluation with the recorded settings.
[13]	Different crops and diseases may not be equally represented.	Report class-wise results and identify unsupported classes.	Analyze the confusion matrix and per-class recall.
[14]	Sensor readings and AI predictions may not be synchronized.	Attach timestamps to both data sources.	Check timestamp consistency and missing readings.
[15]	System usefulness may be claimed without a baseline comparison.	Compare the integrated workflow with image-only predictions.	Evaluate information completeness, processing time and recommendation correctness.
[16]	Field performance may vary with terrain and robot movement.	Test the rover in a controlled outdoor setup before broader field trials.	Record movement reliability, image quality and interruptions.
[17]	Recommendations may not be appropriate for every crop.	Make recommendations crop-specific where reliable guidance is available.	Review each rule against an appropriate agricultural reference.
[18]	A prototype may be described as autonomous before navigation is implemented.	Clearly distinguish operator-controlled movement from autonomous navigation.	Demonstrate the actual control mode and document its limits.

Table 1. Comparative summary of related work

III. PROBLEM STATEMENT

Farmers often rely on manual inspection to identify visible signs of crop diseases and monitor environmental conditions. This process can be time-consuming and may make it difficult to monitor all areas of a field regularly. Image-based disease detection can help recognise disease categories supported by a trained model. However, analysing plant images alone cannot provide information about soil moisture, local temperature, or water availability.

These limitations highlight the need for an affordable crop-monitoring system that combines computer vision with environmental sensing. Such a system should capture plant images, predict supported disease categories, measure selected environmental conditions, and present the results in a clear and understandable format. This information can help users identify potential crop-health issues and determine when further inspection or action may be required.

To address this need, the proposed agricultural robot will combine an existing YOLOv8-based model with a mobile camera platform and an ESP32-based environmental monitoring module. The camera will capture plant images for analysis, while the sensors will collect environmental measurements. The results will be presented through a dashboard



to support crop monitoring and basic decision-making. The effectiveness of the complete system will be assessed after hardware integration and testing under real agricultural conditions.

IV. OBJECTIVES

The main objectives of the proposed system are:

- To use the existing YOLOv8-based model for predicting supported crop-disease classes from plant images.
- To develop a low-cost, four-wheel agricultural robot for close-range plant monitoring.
- To capture plant images using a camera mounted on the robot.
- To perform image inference on a laptop using the existing trained model.
- To integrate an ESP32-based module for collecting soil-moisture and environmental readings.
- To monitor air temperature, relative humidity, rain presence, and water-tank level using suitable sensors.
- To develop a dashboard displaying disease predictions, sensor readings, and scan history.
- To generate basic rule-based alerts and recommendations using model outputs and sensor readings.
- To evaluate the model and integrated hardware separately using controlled images and real-world plant images.

V. PROPOSED SYSTEM

The proposed agricultural robot consists of four primary modules: the mobile robotic platform, the image-processing module, the environmental-monitoring module, and the recommendation dashboard.

A. Mobile Robotic Platform

The mobile platform consists of a four-wheel chassis, DC geared motors, wheels, a battery supply, a motor driver, and a compatible microcontroller. A camera will be mounted on the chassis to capture plant images at close range.

The initial prototype will use manual movement control. The operator will move the robot between plants and position the camera to capture suitable images. Autonomous navigation and GPS-based route planning are not included in the initial implementation.

B. Image-Processing Module

The image-processing module uses the existing YOLOv8-based crop-disease model. Images captured by the camera are transferred to a laptop, where the model performs inference.

The system will display the predicted class and the associated model confidence score. Only disease classes supported by the trained model will be reported. If the model returns an uncertain prediction, the system should allow the operator to capture another image or request expert inspection.

C. Environmental-Monitoring Module

An ESP32 development board will collect readings from the planned environmental sensors. The sensor module will monitor:

Soil moisture using a capacitive soil-moisture sensor.

Air temperature and relative humidity using a suitable temperature/humidity sensor.

Rain presence using a rain-detection module.

Water-tank level using a float switch.

The ESP32 will transmit readings to the laptop through USB serial communication or Wi-Fi. Sensor readings will require suitable calibration before being used for crop-specific recommendations.

D. Recommendation and Dashboard Module

The dashboard will combine the machine-learning prediction with the latest available sensor readings. It will display the predicted disease class, confidence score, environmental measurements, timestamps, and alerts.

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DOI: 10.48175/IJARSCT-40322



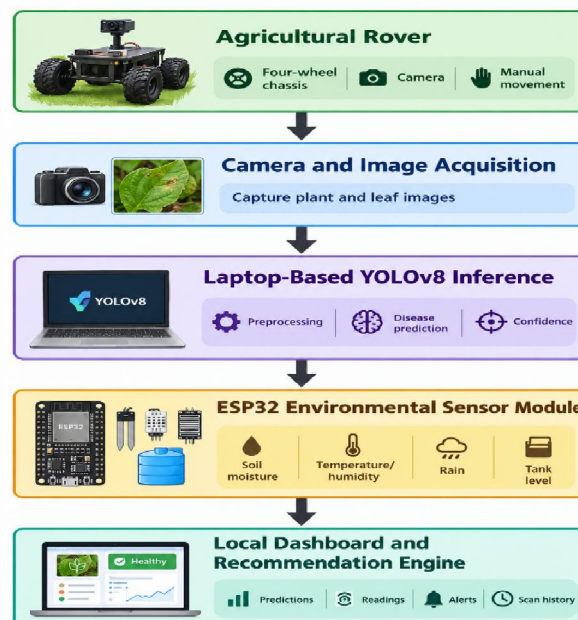
The recommendation module will initially use predefined rules. For example, low calibrated soil-moisture readings may trigger an irrigation-check alert, while a low water-tank level may trigger a refill alert. These recommendations will be advisory and must be configured according to the crop, soil, and sensor calibration.



Fig. 7. Sample dashboard showing prediction, sensor readings and recommendation.

VI. SYSTEM ARCHITECTURE

The proposed system follows a modular architecture in which image processing and environmental sensing operate as separate data-collection paths and share information through a local dashboard.



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The camera sends images to the laptop for inference, while the ESP32 collects sensor measurements. The dashboard combines these outputs to support crop monitoring. The diagram represents the proposed design; the complete hardware-to-dashboard connection remains to be implemented.



VI. HARDWARE AND SOFTWARE REQUIREMENTS

The following table lists the proposed hardware components. These are planned components, not confirmation that the hardware has already been assembled.

Hardware component	Purpose
Four-wheel robot chassis	Supports movement across the ground
DC geared motors and wheels	Provide robot movement
Motor driver, such as L298N	Controls motor direction and speed
Arduino-compatible controller or ESP32	Controls movement and/or reads sensors, depending on the final wiring design
Laptop	Runs the YOLOv8 model and dashboard
USB webcam or compatible camera	Captures plant images
ESP32 development board	Collects sensor readings and communicates with the laptop
Capacitive soil-moisture sensor	Estimates soil moisture after calibration
DHT22 or equivalent sensor	Measures air temperature and relative humidity
Rain-detection module	Detects water on the sensing plate
Water-level float switch	Indicates a configured tank-water level
Battery, wiring and enclosure	Power and protect the electronic components

Software requirements

Python for the inference and sensor-communication workflow.

YOLOv8 for the existing crop-disease model.

OpenCV for image capture and processing.

ESP32-compatible development tools and firmware.

A local dashboard developed using a suitable framework, such as Streamlit or a web interface.

CSV or a lightweight database for storing scan history and sensor readings.

VII. METHODOLOGY

The project methodology consists of the following stages.

A. Dataset Preparation

The PlantVillage dataset is used to train and evaluate the disease detection model. It contains labelled images of healthy plants and plants affected by different diseases. Before training, the images are prepared and resized according to the input requirements of the selected YOLOv8 model.

The dataset is divided into training, validation, and testing subsets based on the existing training workflow. The experimental report should specify how the dataset was divided, the number of images in each subset, the distribution of images across disease classes, the preprocessing steps, and the model configuration.



A. Dataset Preparation

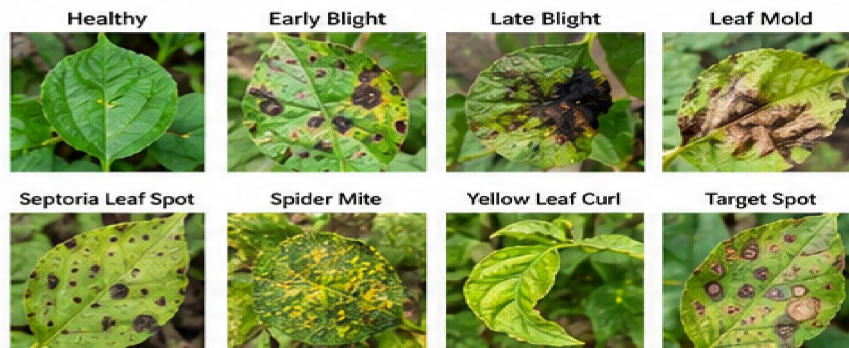


Fig. 1. Sample images from the PlantVillage dataset showing healthy and diseased plant leaves.

B. Model Training and Evaluation

The project team has already trained and tested the YOLOv8-based model using the prepared dataset. The model achieved a reported test accuracy of 99.76% on the current test set. This result represents the model's performance on that dataset and should not be interpreted as its accuracy under real-world conditions.

The final report should describe the test dataset, evaluation method, and metric used to calculate this value. The trained model will be used in the proposed robot prototype. Additional training is not necessary simply to connect the model to the robot. However, fine-tuning may be considered if testing with real-field images reveals a significant difference in performance.

B. Model Training and Evaluation

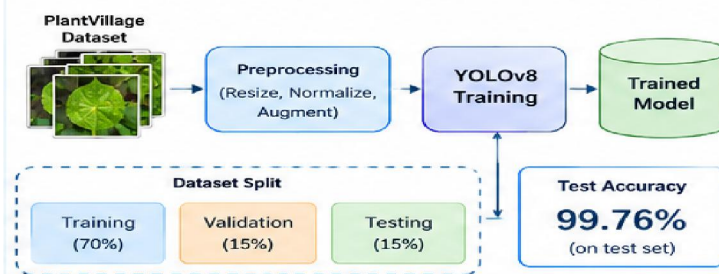


Fig. 2. YOLOv8 model training and evaluation workflow with dataset split and reported accuracy.

C. Robot Assembly

A four-wheel chassis will be assembled using DC motors, wheels, a motor driver, and a suitable battery. A camera will be mounted on the chassis at an appropriate height and angle to capture clear images of plant leaves.

Initially, the robot will be operated manually. Its basic movements, including forward, reverse, left, right, and stop, will be tested individually to ensure that the motors and motor driver function correctly. Once these movements are working reliably, the camera and AI-based disease detection workflow will be connected to the system.



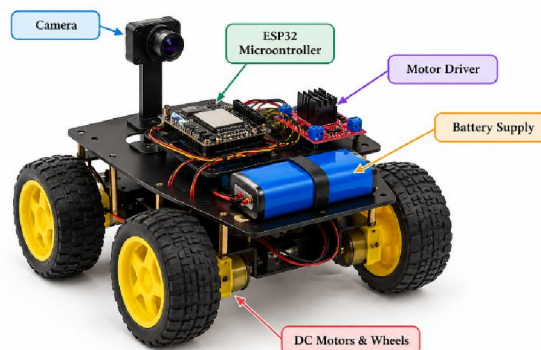
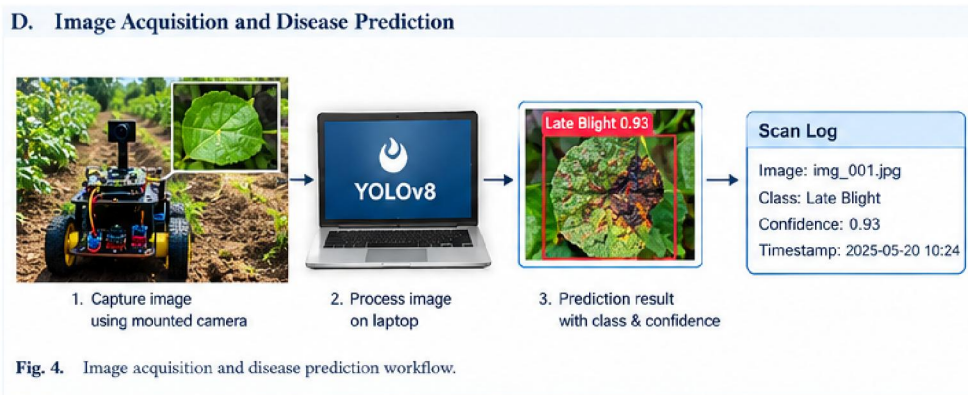


Fig. 3. Four-wheel robot chassis with camera, ESP32, motor driver, and battery supply.

D. Image Acquisition and Disease Prediction

The operator will position the robot near a plant and use the mounted camera to capture images of its leaves. The captured images will be transferred to the laptop, where the trained YOLOv8 model will process them and predict the corresponding disease class or healthy class, along with a confidence score.

When scan logging is enabled, the system will record the image location, predicted class, confidence score, and timestamp for future reference. Images collected during real-field testing will be kept separate from the original training dataset to help evaluate the model's performance on images it has not previously encountered.

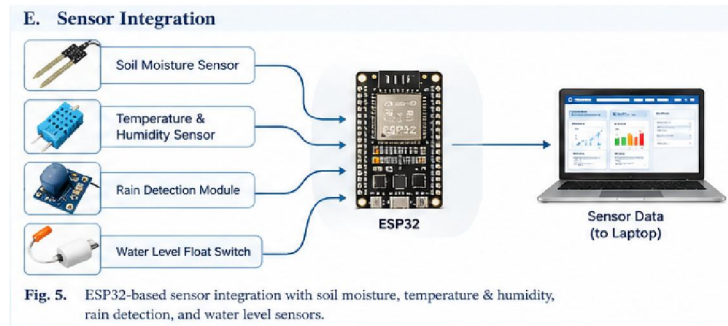


E. Sensor Integration

An ESP32 microcontroller will be connected to the soil-moisture sensor, temperature and humidity sensor, rain-detection module, and water-level float switch. The ESP32 will collect readings at predefined intervals and transmit the measurements to the laptop for display and further processing.

Each sensor will be tested to check whether it provides suitable readings under the intended operating conditions. The soil-moisture sensor will be calibrated for the soil in which it will be used. The temperature and humidity sensor will be compared with a reference device, where available. The rain sensor will be tested using controlled water exposure, and the float switch will be checked to confirm that it detects the configured water level correctly.



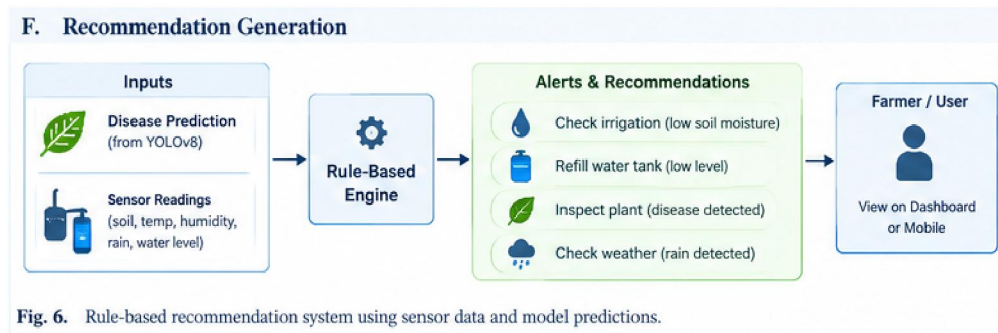


F. Recommendation Generation

A rule-based recommendation module will interpret the available sensor readings and disease predictions to generate alerts for the user. Each alert will indicate the condition that triggered it and include the relevant sensor reading or model prediction wherever applicable.

For example, a low soil-moisture reading may generate an alert asking the farmer to check whether irrigation is required. Similarly, a low water-level reading from the float switch may trigger a tank-refill notification. If the model predicts a plant disease, the system may recommend inspecting the affected plant more closely and consulting a verified, crop-specific disease management reference.

These recommendations are intended to support the farmer's decision-making process. They will not be treated as confirmed diagnoses or guaranteed treatment instructions, as the final decision should consider the actual crop condition and other relevant field observations.



VIII. WORKING PRINCIPLE

The proposed system will operate through the following steps:

Rover positioning: The operator manually moves the agricultural rover near the plant that needs to be inspected.

Image capture: The camera captures an image of the plant or its leaf, ensuring that the image is clear enough for analysis.

Image transfer: The captured image is transferred to the laptop for processing.

Disease prediction: The existing YOLOv8-based model analyses the image and predicts the most likely disease class among the classes it was trained to recognise. It also provides a confidence score for the prediction.

Environmental data collection: The ESP32 reads the connected sensors, including soil moisture, temperature, relative humidity, rain presence, and water tank level, and sends the readings to the laptop.

Dashboard display: The dashboard presents the disease prediction, confidence score, and available environmental measurements in one interface.



Alert generation: The rule-based recommendation module compares the sensor readings with predefined thresholds and generates alerts when specified conditions are detected.

Data storage: The image prediction and its associated sensor readings can be saved for future review and comparison.

Initially, the rover will be controlled manually, while image analysis and environmental monitoring will be performed by the connected system. Autonomous navigation and automatic field coverage are planned as possible future improvements and will not be considered implemented features unless they are developed and tested successfully.

IX. RESULTS AND DECISION

The completed work currently includes the development and testing of the YOLOv8-based crop-disease detection model using the PlantVillage dataset. The project team obtained a test accuracy of 99.76% on the current test set.

This result represents the model's performance on the evaluation dataset used during testing. It does not guarantee the same level of accuracy under actual agricultural conditions. Images captured in the field may vary in lighting, background, camera distance, leaf orientation, disease severity, and image quality. These variations may affect the model's predictions and require further evaluation using images collected from real farms.

The physical rover, environmental-sensor integration, and dashboard are still planned for development. Therefore, results for rover movement, camera-to-model processing, sensor measurement accuracy, dashboard response time, and disease-detection performance in real fields are not yet available. These aspects cannot be evaluated conclusively until the complete system has been assembled and tested.

The next phase will involve assembling the rover, mounting the camera, connecting the environmental sensors to the ESP32, and integrating the components with the dashboard. The sensors will be calibrated, and the integrated system will be tested using new plant images collected under different field conditions. The recommendation module will also be evaluated to determine whether its threshold-based alerts respond appropriately to the measured environmental conditions.

X. ADVANTAGES OF PROPOSED SYSTEM

Low-cost development: The proposed design uses a simple ground-based rover and an existing laptop to perform AI-based image analysis, reducing the need for specialised onboard computing hardware.

Close-range image capture: The operator can position the camera near plant leaves to capture images for disease analysis.

Machine-learning-based detection: The YOLOv8 model predicts disease classes represented in its training data and provides a confidence score for each prediction.

Environmental monitoring: The system is designed to collect soil-moisture, air-temperature, relative-humidity, rain-presence, and water-tank-level readings.

Centralised dashboard: A single interface will allow users to view disease predictions and environmental measurements together.

Modular architecture: The camera, AI model, environmental sensors, rover movement, and dashboard can be developed and tested as separate modules before integration.

Scope for future expansion: The design can be extended to include GPS-based field location records, additional sensors, and navigation assistance.

Simpler operation than a drone-based system: A ground rover avoids drone-specific requirements such as flight controllers, propellers, and flight-safety measures, although it still requires suitable mobility, power, and operational safety arrangements.

These advantages describe the expected benefits of the proposed design. Their practical effectiveness, including cost, reliability, and usefulness under field conditions, will need to be established through hardware integration and experimental testing.



XI. APPLICATIONS

The proposed agricultural robot may support the following applications:

- Preliminary identification of visible crop-disease symptoms.
- Close-range crop and leaf image collection.
- Basic soil-moisture monitoring.
- Local temperature and relative-humidity monitoring.
- Rain-presence alerts.
- Water-tank-level alerts for irrigation planning.
- Recording plant images, predictions and sensor readings.
- Educational demonstrations of AI and IoT applications in precision agriculture.
- Future integration with crop-specific advisory systems.
- The current prototype does not independently diagnose all plant diseases, measure nutrient concentrations, predict yield or automatically apply treatments.

XII. LIMITATIONS

The proposed system has several limitations.

- First, the robot requires manual operation in its initial implementation. Autonomous navigation, obstacle avoidance and GPS-based field mapping are not yet available.
- Second, the YOLOv8 model has been evaluated using the existing PlantVillage test set. Its performance on real-world field images remains to be established.
- Third, low-cost soil-moisture sensors require calibration for the soil type and installation conditions. Temperature, humidity and rain readings provide environmental information but do not independently establish the cause of a plant disease.
- Fourth, the water-level float switch provides a threshold indication rather than a continuous measurement of tank volume. A rain-detection plate identifies water at its surface but does not measure rainfall in millimetres or forecast future rainfall.
- Finally, the recommendation engine will initially use predefined rules. The usefulness of these recommendations will depend on appropriate crop-specific thresholds, sensor reliability and verified management guidance.

XIII. FUTURE SCOPE

Future development can extend the system in several directions:

- Autonomous navigation: Add appropriate sensors and control logic for following crop rows and avoiding obstacles.
- GPS-based field mapping: Record approximate plant locations and associate scans with field coordinates.
- Improved field-image performance: Evaluate the model on field-collected images and fine-tune it if necessary.
- Advanced environmental monitoring: Add additional calibrated sensors where there is a clear agricultural need.
- Crop-specific recommendations: Incorporate verified crop-management information and locally appropriate thresholds.
- Historical analysis: Store scan and sensor data to help users review changes over time.
- Mobile or cloud dashboard: Allow remote access to reports when connectivity is available.
- Automated irrigation integration: Consider connecting the system to irrigation controls only after appropriate testing and safeguards.



- Expanded disease coverage: Add new disease classes only after obtaining suitable labelled data and evaluating the resulting model.
- These features are proposed future enhancements and should not be described as completed components of the current prototype.

XIV. CONCLUSION

This paper presents a proposed low-cost, ground-based agricultural robot for crop-disease detection and environmental monitoring. The design reuses an existing YOLOv8-based model trained and evaluated using the PlantVillage dataset. The project team reports a test accuracy of 99.76% on its current test set. A four-wheel rover and camera will provide a mobile platform for close-range image capture, while a laptop will perform disease inference.

The proposed ESP32-based sensor module will monitor soil moisture, air temperature, relative humidity, rain presence and water-tank level. A local dashboard will combine these measurements with disease predictions to provide basic rule-based alerts and recommendations. At the current stage, the machine-learning model has been tested on images, while the rover, sensor network, dashboard integration and field evaluation remain pending.

The modular design provides a practical development path for a student-level precision-agriculture prototype. However, real-field evaluation, sensor calibration and integrated system testing are necessary before the project's reliability and agricultural benefits can be established.

ACKNOWLEDGMENT

The authors express their gratitude to the Department of Information Technology, Sandip Institute of Technology and Research Centre (SITRC), Nashik, for providing academic guidance and support during the development of this project. The authors also thank their project guide and faculty members for their valuable suggestions and encouragement.

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