Annexure3b- Complete filing

INVENTION DISCLOSURE FORM

Details of Invention for better understanding:

1. TITLE: AI Powered Crop Intelligence Rover.

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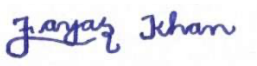
	Signature (Mandatory)	

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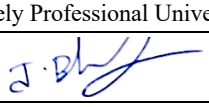
	Signature (Mandatory)	

3. DESCRIPTION OF THE INVENTION:

The present invention, entitled “AI-Powered Crop Intelligence Rover,” relates to an integrated agricultural inspection and decision-support system combining mobile robotics, Internet of Things (IoT) sensing, and artificial intelligence (AI). It comprises a four-wheel-drive (4WD) rover controlled by an ESP32 microcontroller and fitted with a four-degree-of-freedom (4-DOF) articulated robotic arm operated through a PCA9685 servo controller. An ESP32-CAM module equipped with an OV2640 camera is mounted on the arm to capture close-range images of accessible upper and lower leaf surfaces from different angles. A separate sensing unit incorporates a DHT11 sensor for temperature and humidity, a capacitive soil moisture sensor, rain and water-level sensors, and a NEO-6M GPS module for geographical positioning.

The captured images are transmitted to a backend server for computer vision analysis using multiple models. EfficientNetV2-S performs crop disease classification, temperature scaling calibrates prediction confidence, and Grad-CAM provides visual explanations of the classification results. A modified YOLO26 model localises candidate symptom regions, while Mobile-UNet performs pixel-level lesion segmentation. Separately, a 12-rule environmental assessment engine evaluates sensor readings for potential heat stress, soil moisture stress, and waterlogging, generating risk alerts and irrigation advisories. A Random Forest model recommends suitable crops from 22 classes using its configured environmental inputs.

A Python-based FastAPI backend coordinates communication between the hardware, analytical models, and user interfaces. The results are presented through a browser-based dashboard displaying image-analysis outputs, sensor readings, environmental alerts, and crop recommendations. The operator can control rover movement and robotic arm positioning through a mobile-accessible browser interface. The system also incorporates an ESP32-based XiaoZhi multilingual voice assistant, which retrieves supported sensor readings and crop analysis information through read-only backend services.

A. PROBLEM ADDRESSED BY THE INVENTION:

Farmers must regularly inspect crops for diseases, pest damage, and other conditions affecting plant growth. However, large fields, dense foliage, overlapping leaves, and varying plant heights make individual plant inspection time-consuming and can conceal early symptoms. Similar visible symptoms across different diseases further complicate identification, particularly for farmers with limited access to agricultural support.

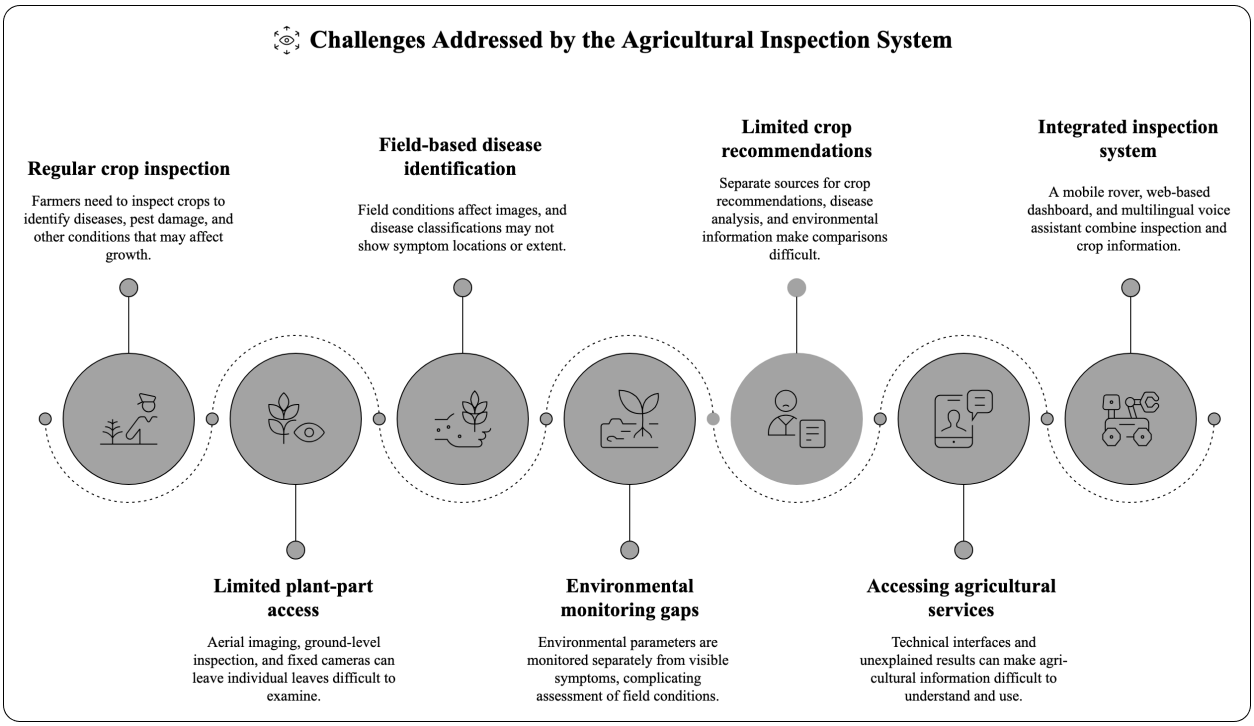


Fig. 1. Seven challenges in crop inspection, from limited access to individual leaves to the lack of a single integrated tool, and the integrated rover system proposed to address them.

Limited Access to Individual Plant Parts During Inspection

Aerial imaging gives a view of the whole field but may miss symptoms on individual leaves, particularly where foliage overlaps. Walking the rows to check plants by hand takes time, and a fixed camera can only view what lies in front of it. A mobile platform that carries an adjustable camera can move to the plant and change its viewing angle, which is the approach taken in this invention.

Limitations of Visual Crop Disease Identification

Lighting, shadows, camera angle and background objects change how a leaf appears in a field photograph, and this variation affects disease analysis. A classifier also returns a single disease category for the whole image. It does not show where the symptoms are or how much of the leaf they cover. For this reason the invention adds symptom localisation and lesion segmentation to the classification step, so that the operator can see which regions of the leaf to inspect further.

Lack of Environmental Monitoring and Crop Risk Assessment

Temperature, humidity, soil moisture and water availability all affect crop growth, yet they are usually measured separately from the visual check of the plant. Without regular readings, heat stress, moisture deficiency and waterlogging are easy to miss. A reading can point to a possible

risk but cannot confirm a disease on its own, while a visual check cannot detect the conditions behind a risk. The two kinds of information therefore complement each other.

Limited Access to Crop Recommendations and Agricultural Information

Choosing a crop means matching local conditions to what each crop requires. Farmers with limited access to crop-suitability information face a harder choice, and the difficulty grows when disease analysis, environmental readings and crop recommendations each come from a different source. Comparing them in order to plan what to grow then becomes hard.

Difficulty in Accessing Technology-Based Agricultural Services

Dashboards, prediction scores and mobile applications can be hard for some farmers to read and navigate, and sensor values or AI outputs shown without an explanation are less useful still. Spoken interaction lowers this barrier. The voice assistant in this invention gives access to supported sensor readings and crop analysis information through speech in English, Hindi and Punjabi.

Need for an Integrated and Farmer-Friendly Inspection System

These problems point to the need for an operator-controlled mobile system that takes close-range plant images, analyses visible symptoms, measures environmental conditions and recommends suitable crops. The invention combines these functions in one rover, a web dashboard and a multilingual voice assistant, so that crop inspection and crop-related information can be used without specialised technical knowledge.

B. OBJECTIVE OF THE INVENTION

The invention has the following objectives:

1. To build a four-wheel-drive (4WD) agricultural rover with a four-degree-of-freedom (4-DOF) robotic arm that can inspect accessible upper and lower leaf surfaces at close range, at different heights and angles.

2. To let an operator control rover movement and robotic arm positioning from a web browser on a computer or smartphone.

3. To capture plant images using an ESP32-CAM module with an OV2640 camera and transmit them to a server for computer vision analysis.

4. To implement a computer vision pipeline for disease classification, confidence calibration, symptom localisation, lesion segmentation, and Grad-CAM-based visual explanation.

5. To collect environmental measurements, including temperature, humidity, soil moisture, rainfall-related conditions, and water level, along with GPS-based location information.
6. To implement a rule-based environmental assessment system to identify potential heat stress, soil moisture stress, and waterlogging and generate risk alerts and irrigation advisories separately from visual disease analysis.

7. To develop a Random Forest-based crop recommendation model that uses configured environmental parameters to recommend suitable crops from 22 classes.

8. To integrate rover control, image analysis, environmental monitoring, and crop recommendation through a common backend, a web dashboard, and a multilingual XiaoZhi voice assistant supporting spoken interaction in English, Hindi, and Punjabi.

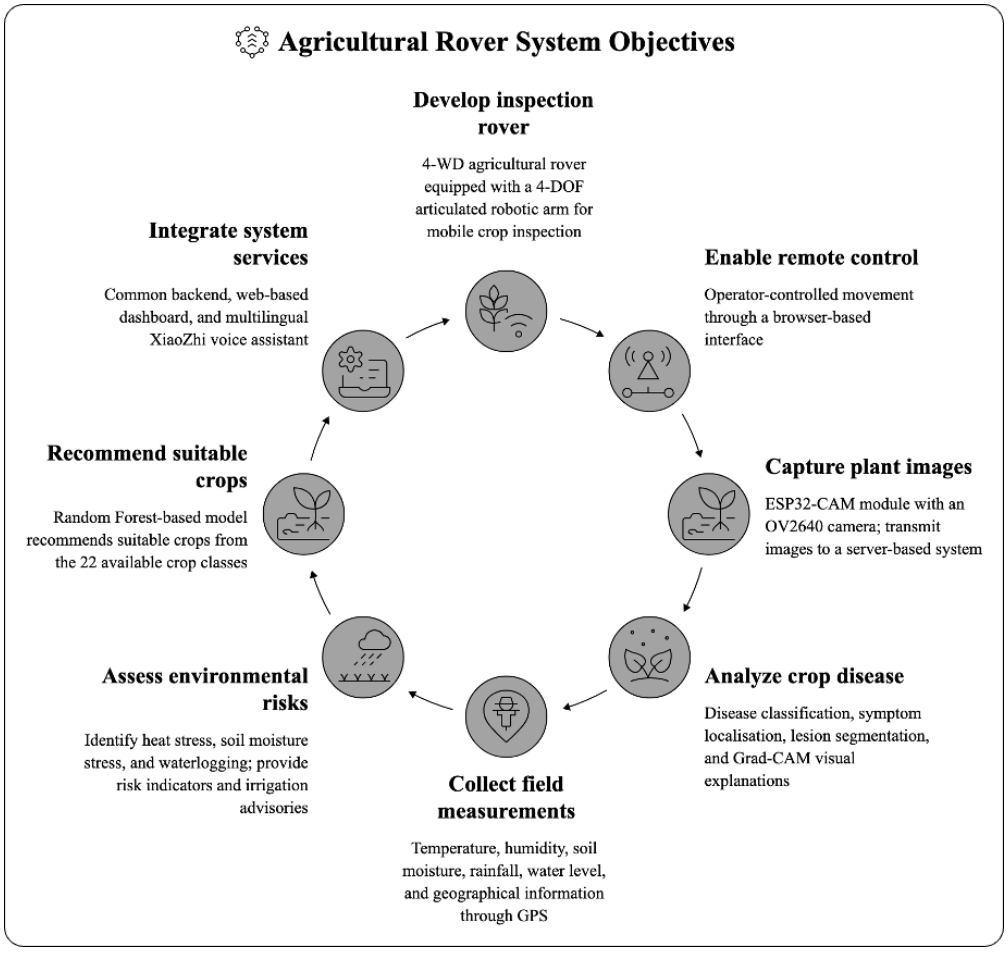


Fig. 2. Overview of the agricultural rover system objectives, illustrating the integrated workflow for crop inspection, image analysis, environmental assessment and crop recommendation.

C. STATE OF THE ART/ RESEARCH GAP/NOVELTY:

Table I. Novelty matrix and comparison with existing patents

Sr. No.	Patent ID	Abstract	Research Gap	Novelty
1.	US12277762B1	It describes a mobile agricultural robot equipped with a camera, GPS, a navigation system, and wireless communication capabilities. The robot uses a CNN-based model, including YOLO, to identify plant types and diseases from captured images. It then transmits the results, along with plant location information, to a mobile device.	The invention focuses on mobile image capture, disease identification, and location reporting. It does not describe the proposed combination of an articulated camera-positioning arm, multi-stage visual analysis, separate environmental risk assessment, crop recommendation, and multilingual voice-based interaction.	The proposed invention combines an operator-controlled 4WD rover with a 4-DOF articulated arm for close-range leaf inspection. It integrates EfficientNetV2-S classification, Grad-CAM visual explanations, YOLO-based symptom localisation, and Mobile-UNet lesion segmentation with environmental risk assessment, crop recommendation, and multilingual voice assistance.
2.	IN416719B	It describes an agricultural robot with a chassis, adjustable parallel-link arms, a body assembly, and a robotic arm. The robotic arm is designed to perform tasks such as crop disease identification, pesticide spraying, soil sampling, and harvesting using the robot's sensor and robotic systems.	The invention focuses on a robotic platform for performing multiple agricultural operations. It does not describe the proposed arrangement for close-range leaf imaging using an articulated camera arm, combined with server-based disease analysis, environmental risk assessment, crop recommendation, and multilingual farmer assistance.	The proposed invention uses an articulated arm specifically to position the imaging camera during crop inspection. Its focus is on crop monitoring and decision support through computer vision, environmental assessment, crop recommendation, and voice-based access to information, rather than automated spraying or harvesting.
3.	US20210048822A1	It describes a mobile agricultural platform equipped with plant-monitoring sensors, a vehicle-control system, and an application mechanism for applying chemical pesticides and biological control agents. Sensor information is used to determine when and where treatment should be applied.	The disclosed system focuses on mobile crop monitoring combined with targeted treatment application. It does not describe the proposed combination of articulated close-range camera inspection, multi-stage computer vision analysis, a separate rule-based environmental risk engine, crop recommendation, and multilingual voice-based information access.	The proposed invention focuses on crop inspection and decision support rather than treatment application. It combines an articulated imaging arm, multiple computer vision methods, environmental risk assessment, and a Random Forest-based crop recommendation model, with results accessible through a dashboard and a voice assistant.
4.	US20240345053A1	It describes a mobile crop-monitoring system with an imaging device and a leaf-bending mechanism that	The disclosed approach focuses on autonomous crop monitoring and exposing leaves during	The proposed invention uses an operator-controlled ground rover and an articulated

		improves access to plant parts during image capture. The disclosed embodiments include aerial and terrestrial platforms for inspecting crops and identifying conditions that require attention.	image capture. It does not describe the proposed operator-controlled 4WD rover equipped with a servo-operated 4-DOF camera arm and integrated with disease classification, symptom localisation, lesion segmentation, environmental risk assessment, and crop recommendation.	robotic arm to position the camera at different angles. It combines this inspection arrangement with server-based visual analysis, sensor-based environmental assessment, crop recommendation, and multilingual voice assistance.
5.	IN202121010953A	It describes an agricultural monitoring system that combines environmental sensors, a camera, wireless communication, a server, a database, and CNN-based analysis. The system collects readings such as soil moisture, temperature, humidity, and rainfall, generates alerts, and provides agricultural advice. It also communicates alerts and advice in a language selected by the farmer.	The published application addresses IoT monitoring, CNN-based crop analysis, and communication in a selected language. However, it does not describe the proposed combination of an articulated mobile imaging rover, multi-stage visual analysis involving detection and segmentation, a separate rule-based environmental risk engine, and conversational voice-based access to live system information.	The proposed invention combines mobile robotic leaf inspection with classification, Grad-CAM visual explanations, symptom localisation, and lesion segmentation. It also includes a separate environmental risk assessment mechanism and a crop recommendation model. Its XiaoZhi assistant provides spoken access to available sensor readings and crop analysis information in English, Hindi, and Punjabi.
6.	IN202441051187A	It describes an IoT- and machine-learning-based crop selection system that uses environmental and soil-related parameters to recommend suitable crops. The disclosed inputs include temperature, rainfall, humidity, nitrogen, phosphorus, potassium, pH, electrical conductivity, and CO_2. Sensor readings are used for crop selection analysis.	The published application focuses primarily on crop selection using environmental and soil-related information. It does not describe a mobile robotic inspection platform, articulated camera positioning, image-based disease classification, symptom localisation, lesion segmentation, or multilingual voice-based farmer assistance.	The proposed invention includes crop recommendation as part of a broader agricultural inspection system. It combines a mobile imaging rover, multi-stage computer vision analysis, independent environmental risk assessment, and a Random Forest model covering 22 crop classes. The results can also be accessed through a web dashboard and a multilingual XiaoZhi voice assistant.

D. DETAILED DESCRIPTION:

1. Overview of the Invention

The present invention, entitled “AI-Powered Crop Intelligence Rover,” relates to an integrated agricultural inspection and decision-support system combining mobile robotics, Internet of Things (IoT) sensing, artificial intelligence (AI), computer vision, and a web-based monitoring interface.

The system assists in crop inspection by capturing close-range plant images, analysing visible symptoms, collecting environmental measurements, and generating crop recommendations.

The proposed system comprises a four-wheel-drive (4-WD) mobile rover, a four-degree-of-freedom (4-DOF) articulated robotic arm, an ESP32-CAM imaging unit, an environmental sensing unit, a server-side processing system, a browser-based control and monitoring interface, and a multilingual XiaoZhi voice assistant.

The rover operates under user control and positions the imaging unit near selected plants for image capture. The captured images are transmitted to the backend, where computer vision models perform disease classification, confidence calibration, visual explanation, symptom localisation, and lesion segmentation. Simultaneously, environmental sensors collect field measurements, which are evaluated by a separate rule-based risk assessment engine. A Random Forest model generates crop recommendations using its configured input parameters.

These functions are integrated through a common software architecture, enabling operators to access crop-related information and system outputs through the web dashboard or the multilingual voice assistant.

2. Six-Layer Cyber-Physical System Architecture

The invention follows a modular six-layer architecture, with each layer performing a specific function and communicating through embedded controllers and backend services.

- **Layer 1: Physical Actuation Layer**
  Comprises the 4WD chassis, four DC geared motors, an L298N motor driver, and a 4-DOF robotic arm for rover movement and camera positioning.
- **Layer 2: Image Acquisition and Environmental Sensing Layer**
  Uses an ESP32-CAM module with an OV2640 camera to capture plant images, while separate sensors collect temperature, humidity, soil moisture, rainfall-related information, and water-level data. A NEO-6M GPS module provides location information.
- **Layer 3: Embedded Control and Telemetry Layer**
  ESP32 controllers manage rover movement, servo positioning, and sensor data acquisition. The PCA9685 controls the arm servos, while Wi-Fi enables communication with the backend and user interfaces.
- **Layer 4: Backend and Communication Layer**
  Uses Python, FastAPI, and Uvicorn to receive data, handle requests, and coordinate processing. Docker Compose manages backend deployment.
- **Layer 5: Deep Learning and Decision-Support Layer**
  Integrates EfficientNetV2-S, temperature scaling, Grad-CAM, modified YOLO26, and Mobile-UNet for image analysis, alongside a Random Forest crop recommendation model and a 12-rule environmental risk assessment engine.

- **Layer 6: Farmer Interface and Visualization Layer**
  Provides a browser-based dashboard for rover control, image-analysis results, sensor readings, environmental alerts, and crop recommendations, supported by a multilingual XiaoZhi voice assistant.

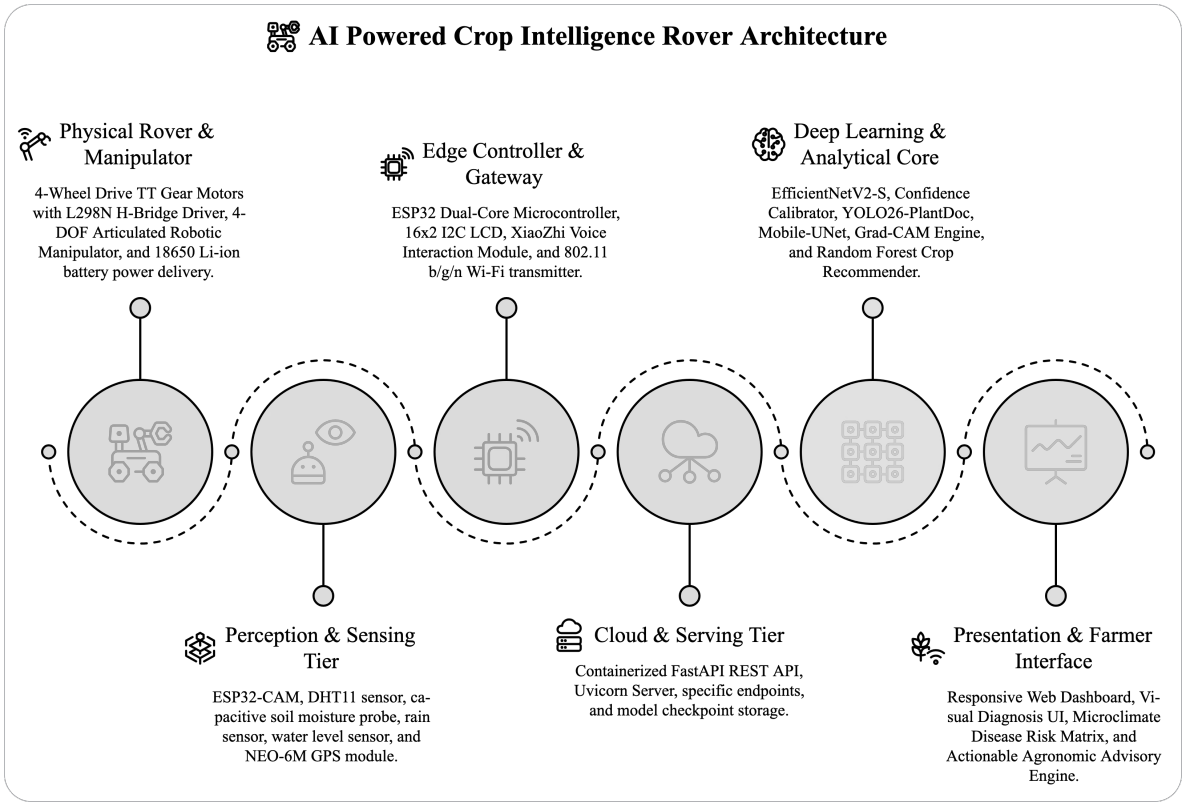


Fig. 3. Six-layer architecture integrating rover hardware, sensing, control, backend processing, AI analysis and farmer interfaces.

3. Mobile Rover and Movement Control Mechanism

The physical platform consists of a four-wheel-drive (4WD) chassis powered by four DC TT geared motors through an L298N dual H-bridge motor driver. An ESP32 controls rover movement using differential steering.

The rover supports forward and reverse movement, left and right pivot turns, 180-degree turns, and full-stop commands. Operators control these functions through a browser-based interface that also provides speed presets and field-row manoeuvre commands, allowing the rover to be positioned near selected plants for inspection.

The rover is operator-controlled and does not currently support autonomous crop-row navigation or obstacle avoidance. A heartbeat-based safety mechanism monitors periodic signals from the control interface and stops motor output when communication is interrupted for longer than the configured timeout period.

4. Four-Degree-of-Freedom Robotic Arm

The rover carries a four-degree-of-freedom (4-DOF) articulated robotic arm whose purpose is to hold the imaging unit at different heights and viewing angles for close-range inspection of accessible foliage. Three MG996R servos and one MG90S servo move the four joints, which are the base, shoulder, elbow and end-effector. A PCA9685 16-channel, 12-bit PWM controller drives the servos and is connected to the ESP32 over I2C.

The operator sets joint positions from the mobile browser interface. The interface also provides calibration controls, a movement speed adjustment and predefined presets such as Safe Home, Canopy High and Foliar Mid. With these controls the camera can be placed to view accessible upper and lower leaf surfaces.

The arm only positions the camera. It is not designed for automated harvesting, pesticide spraying or other crop-handling operations.

5. Image Acquisition and Camera Positioning

The imaging unit comprises an AI-Thinker ESP32-CAM module equipped with an OV2640 camera and mounted on the 4-DOF robotic arm. The operator drives the rover to a selected plant and adjusts the arm until the camera has a suitable view. The camera captures the plant image and the ESP32-CAM sends it to the backend over the configured wireless interface. The ESP32-CAM performs only image acquisition and transmission. The computationally intensive computer vision operations run on the backend, where each image is first prepared to match the input requirements of the model that will analyse it.

6. Environmental Sensing Unit

A separate ESP32-based sensing unit collects the environmental and field measurements. The implemented subsystem consists of the following components:

- **DHT11 temperature and humidity sensor:** measures ambient temperature and relative humidity around the monitored plants.
- **Capacitive soil moisture sensor v1.2:** gives soil moisture readings for assessing moisture conditions.
- **YL-83 rain sensor:** detects rainfall or water on its sensing surface and reports a rainfall-related status.
- **Water-level sensor:** monitors the water level and helps identify possible water accumulation.
- **NEO-6M GPS module:** gives geographical position when a GPS fix is available.
- **16 × 2 I2C LCD:** displays available sensor readings and local system information.

The ESP32-based sensing unit collects environmental measurements and transmits them to the backend. Readings can also be displayed locally on the LCD.

These measurements provide environmental context for crop monitoring and are used by the rule-based risk assessment and crop recommendation components according to their configured input requirements.

The capacitive soil moisture sensor measures moisture-related electrical properties and does not directly measure soil nitrogen, phosphorus, potassium, or pH. Similarly, the rain sensor provides rainfall-related status rather than quantitative rainfall measurements in millimetres.

7. Backend and Software Architecture

The backend is written in Python and uses FastAPI with a Uvicorn server to receive data, handle requests and coordinate processing between the hardware, the analytical models and the user interfaces. Docker Compose manages its deployment.

The ESP32-CAM sends plant images to the backend, and the ESP32-based sensing unit sends environmental readings. The backend runs the computer vision pipeline, the 12-rule environmental engine and the Random Forest model, and returns the results to the web dashboard as a unified response. The voice assistant reads supported sensor readings, alerts and crop analysis results through read-only Model Context Protocol (MCP) tools.

8. Computer Vision-Based Crop Disease Analysis

The computer vision subsystem analyses images captured by the ESP32-CAM or supplied through the web interface. It includes disease classification, symptom localisation, and lesion segmentation, supported by confidence calibration and visual explanation.

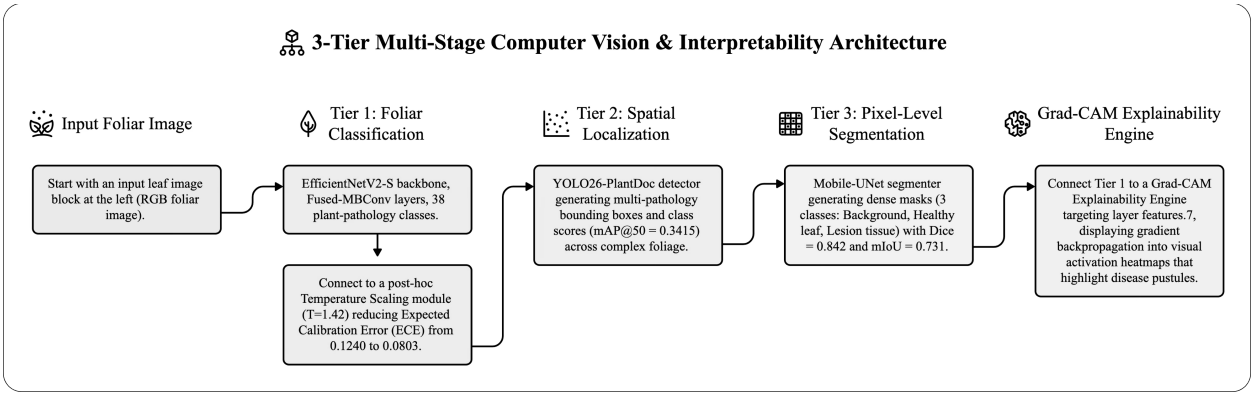


Fig. 4. Three-tier computer vision architecture integrating disease classification, symptom localization, lesion segmentation and Grad-CAM visualization.

8.1 Disease Classification Using EfficientNetV2-S

EfficientNetV2-S assigns each image received by the backend to one of 38 configured crop and disease categories. The image is resized to 256 × 256 pixels and preprocessed before inference. The model outputs the highest-scoring category for the image as a whole. It does not show where the symptoms are or how far they extend.

8.2 Confidence Calibration Using Temperature Scaling

The classification probabilities are calibrated by temperature scaling, using a fitted temperature of T = 1.42 applied before the softmax operation. Evaluated with 15 confidence bins, the expected calibration error (ECE) fell from 0.1240 to 0.0803. Calibration brings the reported confidence closer to the observed accuracy, but it does not guarantee that any individual prediction is correct.

8.3 Visual Explanation Using Grad-CAM

Grad-CAM takes the gradients at the `features.7` convolutional layer and produces a heatmap of the image regions that most influenced the classification. The heatmap is overlaid on the original image. It is an approximate visual explanation. It does not mark exact lesion boundaries and it is not a confirmed diagnosis.

8.4 Symptom Localisation Using Modified YOLO26

A modified YOLO26 model predicts bounding boxes and class labels to localise candidate symptom regions, which adds spatial information to the image-level classification. It was fine-tuned on the PlantDoc detection dataset, which contains 2,581 annotated images in 29 categories. Detection accuracy depends on image quality, annotation quality and the variability of symptoms.

8.5 Lesion Segmentation Using Mobile-UNet

Mobile-UNet performs pixel-level segmentation of visible leaf lesions. It was developed with 260 curated pairs of leaf images and segmentation masks and trained with a combination of Dice loss and binary cross-entropy loss.

The segmentation masks identify leaf and lesion pixels, enabling estimation of the affected leaf area:

$$\textit{Affected Area (\%)} = (\textit{Lesion Pixels} / \textit{Total Leaf Pixels}) \times 100$$

This calculation estimates the proportion of visible leaf area classified as affected. Its reliability depends on image quality and segmentation accuracy.

8.6 Combined Computer Vision Pipeline

The components described above perform complementary functions:

- EfficientNetV2-S predicts the overall disease category.
- Temperature scaling calibrates the classification probabilities.
- Grad-CAM visualises image regions influencing the classification.
- YOLO26 localises candidate symptom regions using bounding boxes.
- Mobile-UNet performs pixel-level lesion segmentation.

The outputs are combined in the dashboard to provide a more detailed representation of the visual analysis than a standalone image classifier can provide.

9. Environmental Risk Assessment

The environmental assessment subsystem operates independently of image-based disease classification. It evaluates sensor readings using a deterministic engine comprising 12 configured agronomic rules to identify potential crop risks, including:

- **Heat Stress:** Evaluates temperature and humidity using a Heat Stress Index based on the Rothfusz regression method.
- **Soil Moisture Stress:** Identifies potential moisture deficiency using soil moisture readings.
- **Flood and Waterlogging Risk:** Uses rainfall-related and water-level readings to assess excessive water accumulation.
- **Irrigation Advisories:** Evaluates environmental and soil moisture conditions to provide irrigation guidance.

The engine compares sensor readings against configured thresholds and generates alerts and advisories through the backend. These outputs indicate potential environmental risks but do not confirm plant diseases or predict crop damage. The system provides recommendations only and does not automatically operate irrigation pumps or valves.

10. Machine Learning-Based Crop Recommendation

The crop recommendation component uses a Random Forest model trained on the `Crop_Recommendation.csv` dataset, which contains 2,200 records across 22 crop classes and seven features: nitrogen, phosphorus, potassium, temperature, humidity, soil pH, and rainfall.

The project evaluated full-feature and reduced-feature configurations. The reduced model uses temperature, humidity, soil moisture and rainfall achieved a cross-validated accuracy of 93.18% across 22 classes.

The model operates independently of disease classification and generates crop recommendations through the backend. Since the rover does not directly measure all seven dataset features, training and runtime inputs must use consistent definitions, units, and preprocessing. Soil moisture and rain-status readings must not be substituted for different physical measurements without validated transformations.

The recommendations support crop planning but do not guarantee crop suitability or yield under all field conditions.

11. Web-Based Monitoring Dashboard

The web-based dashboard provides a unified interface for viewing environmental readings, crop recommendations, and plant disease analysis results. The environmental monitoring section displays available sensor data, including temperature, relative humidity, soil moisture, and rain status, along with environmental risk alerts and crop recommendations.

The plant vision section allows users to submit images and view predicted disease categories, confidence estimates, Grad-CAM visualisations, and available detection or segmentation results. The dashboard also presents system status information, integrating outputs from the hardware and backend modules.

Deployed dashboard: https://aipoweredcropintelligencerover.dpdns.org

12. Mobile Web Teleoperation and Robotic Arm Control

The rover provides a mobile-friendly browser interface accessible over the local network at agrirover.local. It includes directional movement controls, speed settings, pivot turns, a full-stop command, and a field operations console displaying rover status, event logs, and inspection controls.

The robotic arm interface provides controls for the base, shoulder, elbow, and gripper joints, along with calibration sliders, movement speed settings, positioning presets, and waypoint-related controls. This interface enables mobile operation of the rover and camera without a desktop computer. Its operation depends on the local network connection and communication with the embedded controllers. Displayed servo positions represent commanded positions unless independent position-feedback hardware is installed.

13. XiaoZhi Multilingual Voice Assistant

The system incorporates an ESP32-based XiaoZhi voice assistant for accessing crop-monitoring information through spoken interaction. Its hardware includes an INMP441 I2S microphone, a MAX98357A I2S audio amplifier, an 8-ohm speaker, and a 0.96-inch SSD1306 OLED display. The OLED indicates interaction states such as standby, listening, and speaking.

The assistant supports English, Hindi, and Punjabi. It uses read-only Model Context Protocol (MCP) tools to retrieve sensor readings, environmental alerts, and crop analysis information from the backend. It provides voice-based information access but does not control rover movement or robotic arm positioning, which remain managed through the browser interface.

14. Overall Operational Workflow

The system operates through the following eight stages:

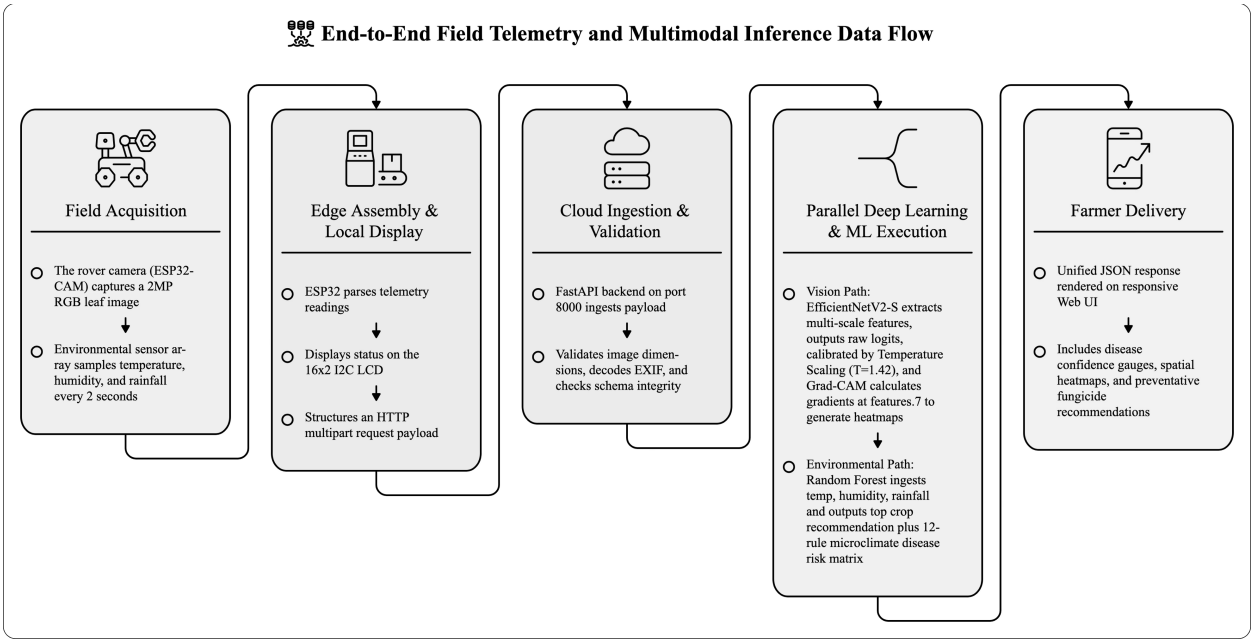


Fig. 5. End-to-end data flow illustrating field acquisition, telemetry processing, backend inference and delivery of agricultural insights.

- **Stage 1: Rover Positioning**
  The operator uses the browser interface to move the rover towards the selected plant using a virtual joystick or directional controls.
- **Stage 2: Robotic Arm Positioning**
  The operator adjusts the four arm joints to position the camera near the target foliage at a suitable viewing angle.
- **Stage 3: Image Acquisition**
  The ESP32-CAM module, equipped with an OV2640 camera, captures the plant image and prepares it for transmission.
- **Stage 4: Sensor Data Collection**
  The ESP32-based sensing unit collects temperature, humidity, soil moisture, rainfall-related information, and water-level readings, along with GPS data when available.
- **Stage 5: Backend Communication**
  The captured image and available system data are transmitted to the backend through the configured communication interfaces.
- **Stage 6: Computer Vision Analysis**
  The backend executes the vision pipeline. EfficientNetV2-S performs disease classification, temperature scaling calibrates confidence, Grad-CAM provides visual

explanations, YOLO26 localises candidate symptoms, and Mobile-UNet performs lesion segmentation.

- **Stage 7: Environmental Assessment and Crop Recommendation**
  The 12-rule environmental engine evaluates sensor readings for potential risks, while the Random Forest model independently generates crop recommendations using its configured inputs.
- **Stage 8: Result Presentation and Voice Interaction**
  The dashboard displays image-analysis results, sensor readings, environmental alerts, and crop recommendations. The XiaoZhi assistant retrieves supported information through read-only backend services and provides spoken responses.

15. Safety and Operational Boundaries

The system separates physical rover control from backend image analysis and agricultural decision support. A heartbeat-based safety mechanism stops motor output if the control connection is interrupted for longer than the configured timeout period. The robotic arm is operated through the browser interface and servo controller.

The computer vision subsystem analyses submitted images, the environmental engine evaluates sensor readings, and the crop recommendation model processes its configured input features to generate their respective outputs.

These outputs support crop inspection and decision-making but do not replace expert diagnosis or agronomic guidance. The system does not currently support autonomous crop-row navigation, automatic pesticide spraying, or automatic irrigation control.

E. RESULTS AND ADVANTAGES:

1. Experimental Results

The proposed system was evaluated through experiments covering disease classification, confidence calibration, visual explanation, object detection, lesion segmentation and crop recommendation. The results assess the performance of individual analytical components and their integration with the rover hardware and software interfaces.

Table II. Summary of reported experimental performance of the AI Powered Crop Intelligence Rover

Component	Evaluation Metric	Reported Result	Evaluation Context
EfficientNetV2-S	Test Accuracy	95.13%	38-class crop disease classification
EfficientNetV2-S	Macro F1-score	0.9354	Classification test evaluation
MobileNetV2	Test Accuracy	89.41%	Classification baseline
Temperature Scaling	ECE before calibration	0.1240	15-bin calibration evaluation

Temperature Scaling	ECE after calibration	0.0803	Fitted temperature T = 1.42
Modified YOLO26	mAP@50	0.3415	PlantDoc detection task
Modified YOLO26	Inference Latency	16.8 ms/image	GPU evaluation
Mobile-UNet	Dice Score	0.8420	Lesion segmentation evaluation
Mobile-UNet	Mean IoU	0.7310	Lesion segmentation evaluation
Mobile-UNet	Model Parameters	0.48 million	Model configuration
Mobile-UNet	Model Size	1.9 MB	Saved model footprint
Mobile-UNet	Inference Latency	9.3 ms/image	GPU evaluation
Random Forest	Cross-validated Accuracy	93.18%	Reduced-feature, 22-class crop recommendation

The EfficientNetV2-S classifier achieved 95.13% test accuracy and a macro F1-score of 0.9354, compared with 89.41% accuracy for the MobileNetV2 baseline. Temperature Scaling reduced the Expected Calibration Error (ECE) from 0.1240 to 0.0803, an approximate 35.2% reduction. The modified YOLO26 detector achieved an mAP@50 of 0.3415 on the PlantDoc detection task, indicating scope for further improvement in field-based symptom localisation. Mobile-UNet achieved a Dice score of 0.8420 and mean IoU of 0.7310, with 0.48 million parameters, a 1.9 MB model size and reported GPU inference latency of 9.3 milliseconds per image.

The reduced-feature Random Forest model achieved 93.18% cross-validated accuracy across 22 crop classes. This result is specific to the selected input features and is distinct from the full-feature dataset benchmark.

1.1 Confidence Calibration Results

The classification model's prediction probabilities were evaluated before and after temperature scaling. The fitted temperature parameter was T = 1.42, and the calibration evaluation used 15 confidence bins.

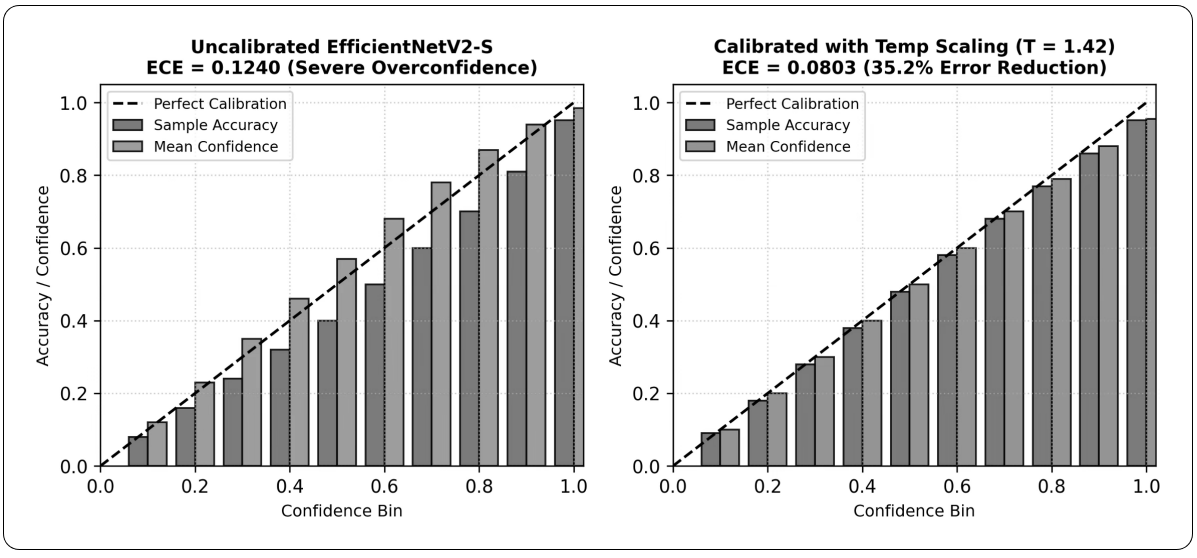


Fig. 6. Reliability calibration curve showing Expected Calibration Error reduction 0.1240 to 0.0803 following temperature scaling with T = 1.42.

1.2 Grad-CAM Visual Explanation Results

Grad-CAM was used to visualise the image regions contributing to the classifier's prediction. The generated heatmap can be compared with visible leaf symptoms to examine the regions influencing the model's output.

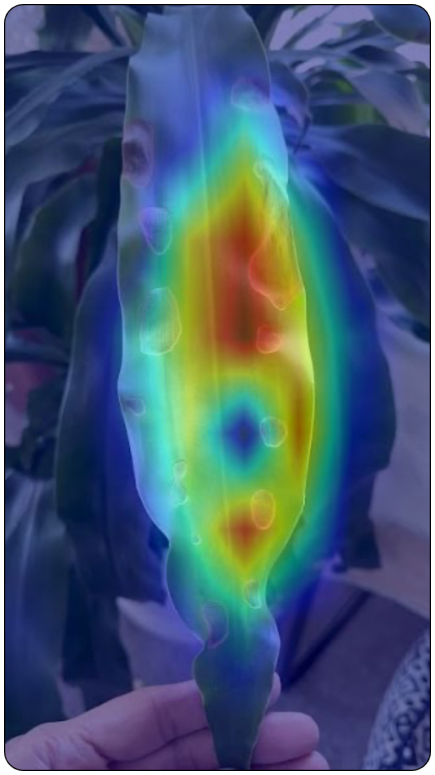


Fig. 7. Grad-CAM heatmap highlighting the leaf regions that influenced the classification.

1.3 Object Detection Results

The modified YOLO26 detector achieved a higher mAP@50 than SSD-MobileNetV2 and YOLOv8n, while Faster R-CNN achieved a higher mAP@50 with greater inference latency.

Table III. Spatial disease localization benchmark on the PlantDoc dataset

Detector Architecture	**Backbone**	**mAP@50**	**Precision**	**Recall**	**Inference Latency**
SSD-MobileNetV2	MobileNetV2	0.2840	0.3120	0.2980	22.4 ms/image
Faster R-CNN	ResNet-50-FPN	0.3800	0.4120	0.3950	98.4 ms/image
YOLOv8n	CSPDarknet	0.3210	0.3680	0.3420	14.5 ms/image
YOLO26-PlantDoc (Proposed)	Modified YOLO26	0.3415	0.3890	0.3650	16.8 ms/image

The proposed YOLO26 configuration achieved a higher mAP@50 than SSD-MobileNetV2 and YOLOv8n, while Faster R-CNN achieved a higher score at the cost of greater inference latency. These results should be interpreted in light of differences in test partitions, input resolutions, hardware, and evaluation protocols.



Fig. 8. Symptom regions predicted by the fine-tuned YOLO26 detection model on PlantDoc images.

1.4 Lesion Segmentation Results

The Mobile-UNet segmentation model was evaluated using curated leaf-image and segmentation-mask pairs. Its results were compared with those of the standard U-Net and SegNet configurations documented in the project report.

Table IV. Semantic lesion segmentation performance

Architecture	Parameters	Model Size	Dice Score	Mean IoU	Inference Latency
Standard U-Net	31.03 M	118.2 MB	0.8550	0.7480	42.5 ms/image
SegNet	29.44 M	112.3 MB	0.8210	0.7020	38.1 ms/image
Mobile-UNet (Proposed)	0.48 M	1.9 MB	0.8420	0.7310	9.3 ms/image

1.5 Crop Recommendation Results

The crop recommendation model was evaluated using the `Crop_Recommendation.csv` dataset, which comprises 2,200 records across 22 crop classes. The dataset contains seven features: nitrogen, phosphorus, potassium, temperature, relative humidity, soil pH, and rainfall. Both full-feature and reduced-feature configurations were evaluated, using seven and three input features, respectively.

Table V. Crop recommendation dataset and reported model performance

Configuration	Input Features	Reported Accuracy	Interpretation
Full-feature Random Forest	Nitrogen, phosphorus, potassium, temperature, relative humidity, soil pH and rainfall	99.55%	Dataset-based benchmark using all seven features
Reduced-feature Random Forest	Three selected features	93.18%	Reported cross-validated result across 22 crop classes

The full-feature Random Forest model achieved 99.55% accuracy using all seven dataset features, while the reduced-feature model achieved 93.18% cross-validated accuracy using three selected inputs. Live deployment requires consistent feature definitions, units, and preprocessing.

2. Prototype Demonstration Results

The assembled prototype demonstrates the integration of the 4WD rover, articulated robotic arm, imaging unit, environmental sensors, backend processing, and user interfaces. Demonstrations include plant inspection, camera positioning, environmental monitoring, and presentation of image-analysis results through the dashboard.

Example outputs include a muskmelon crop recommendation with 66.7% model confidence and a northern leaf blight classification for a corn leaf image with 59.3% model confidence. These are model-generated outputs for the submitted inputs, not confirmation of crop suitability or a disease diagnosis.

3. Advantages of the Proposed Invention

The proposed invention offers the following engineering advantages over systems that rely solely on manual inspection, fixed imaging, standalone disease classification, or separate environmental monitoring tools.

- **Close-range ground-level inspection:** The mobile rover can be positioned near plants and operated around potted specimens or crop rows. Its adjustable camera arm supports different viewing angles and inspection of accessible lower leaf surfaces that may be difficult to examine using fixed overhead imaging.
- **Adjustable imaging position:** The 4-DOF robotic arm provides controlled camera positioning at different heights and angles. This offers greater flexibility during visual inspection than a camera mounted in a single fixed position.
- **Multi-stage computer vision analysis:** The system combines classification, confidence calibration, Grad-CAM, object detection, and lesion segmentation. Each component provides a different type of information about the submitted plant image.

- **Improved confidence interpretation:** Temperature scaling reduces the reported expected calibration error (ECE) under the evaluation conditions. This supports more appropriate interpretation of the model's confidence estimates.
- **Spatial symptom information:** The modified YOLO26 detector provides bounding boxes around candidate symptom regions, while Mobile-UNet provides pixel-level segmentation. These outputs offer additional spatial information beyond an image-level disease category.
- **Environmental context:** The separate sensor subsystem collects temperature, humidity, soil moisture, rainfall-related information, and water-level information. The 12-rule risk assessment engine uses available readings to generate environmental risk indicators and advisories.
- **Crop recommendation:** The Random Forest component uses its configured input features to recommend crops from 22 crop classes. This adds a crop-planning function to the inspection and monitoring system.
- **Integrated monitoring and control:** The browser interface brings rover movement, robotic arm positioning, plant-image analysis, environmental readings, and recommendations together in a common platform.
- **Multilingual voice interaction:** The XiaoZhi assistant provides spoken access to supported sensor readings and crop analysis information in English, Hindi, and Punjabi.
- **Modular and accessible construction:** The physical system uses commonly available embedded controllers, geared motors, servo motors, sensors, and open-source software frameworks. The project report estimates the prototype's component bill of materials at less than USD 65. This is a component-cost estimate, not a verified estimate of the total cost of ownership.

Table VI. Functional comparison of the proposed system with common standalone agricultural monitoring approaches

Capability	Manual or Standalone Approach	Proposed AI Powered Crop Intelligence Rover
Plant inspection	Individual manual inspection or fixed camera position	Operator-controlled ground rover with an adjustable camera arm
Image-based disease analysis	May provide a disease category alone	Classification, confidence calibration, Grad-CAM, detection and segmentation
Symptom localisation	Often not provided by image-level classification	Bounding-box localisation through modified YOLO26
Affected-area estimation	Requires separate visual estimation or analysis	Pixel-level lesion segmentation through Mobile-UNet
Environmental monitoring	Often handled through separate sensor systems	Integrated environmental sensing and 12-rule risk assessment
Crop recommendation	May require separate advisory tools or manual assessment	Random Forest recommendation component covering 22 crop classes
System interaction	Separate applications or technical interfaces	Browser-based monitoring and control with multilingual voice information access

4. Technical and Practical Advantages

The integration of mobile inspection, adjustable imaging, computer vision, environmental sensing, and crop recommendation provides complementary agricultural insights through a unified platform. Its modular architecture allows individual hardware and software components to be upgraded independently. Server-side processing also separates AI inference from embedded rover

control, reducing the computational load on the ESP32 controllers. The prototype demonstrates technical feasibility, while further field testing is required to establish commercial-scale performance and actual improvements in yield or resource use.

F. EXPANSION:

The invention uses a modular hardware and software architecture that can be adapted to different crops, field conditions, sensor requirements, and agricultural applications. The following variations describe possible embodiments and future extensions. Unless stated otherwise, these features are proposed enhancements and are not part of the current prototype.

1. Variable Hardware Configurations

The rover may use alternative chassis designs, including two-wheel-drive, four-wheel-drive, or tracked platforms. The robotic arm may be modified in terms of degrees of freedom, link dimensions, payload capacity, and actuator configuration. Alternative cameras, lenses, illumination systems, depth cameras, thermal cameras, or multispectral imaging devices may also be integrated.

2. Additional Environmental Sensors

The sensing unit may be expanded with soil pH, NPK, electrical conductivity, salinity, leaf wetness, light intensity, solar radiation, wind, CO_2, soil temperature, quantitative rainfall, and water-flow sensors. Additional sensors would require appropriate calibration and validation before use.

3. Alternative AI and Computer Vision Models

The system may incorporate alternative classification, object detection, and segmentation architectures according to accuracy, model size, and computing requirements. Additional crop and disease classes may be supported through expanded datasets and annotations. Model thresholds, preprocessing settings, and environmental assessment rules may also be configured for specific crops and field conditions.

4. Edge Computing and Offline Operation

An onboard computing platform, such as an NVIDIA Jetson Orin Nano or an equivalent device, may support local image processing. Models may be quantised and optimised using frameworks such as TensorRT to reduce dependence on remote processing. Performance would require validation on the selected hardware.

5. Autonomous Navigation

The manually operated rover may be extended with LiDAR, wheel encoders, inertial sensors, and a ROS 2-based navigation system. These additions may support mapping, localisation, obstacle avoidance, autonomous crop-row navigation, and return-to-docking functions, subject to further development and field testing.

6. Extended Communication and Deployment

Communication may be extended through Wi-Fi, Bluetooth Low Energy, LoRa, or cellular networks. The backend may operate locally, in the cloud, or through a hybrid edge-to-cloud architecture. Multi-rover and multi-farm support may also be implemented through additional device-management and data services.

7. Adaptation to Agricultural Environments

The system may be adapted for open fields, greenhouses, polyhouses, nurseries, and controlled-environment farms. Chassis dimensions, sensor configurations, and camera arrangements may be modified according to crop structure and operating conditions. Additional measurements, such as light intensity, CO_2 concentration, and nutrient-solution parameters, may be incorporated where relevant.

8. Targeted Crop Treatment

A future version may incorporate an application mechanism, such as a micro-solenoid sprayer, for targeted treatment of selected plant regions. This would require accurate symptom localisation, camera-to-arm calibration, controlled dosing, crop-specific treatment information, and safety validation. The current prototype does not include automated pesticide or fungicide spraying.

9. Solar-Powered Operation

Solar panels and rechargeable battery systems may be incorporated to extend operating time in locations with limited access to grid electricity. Their configuration would depend on motor and servo loads, camera usage, sensor operation, communication requirements, and the required operating duration.

Table VII. Configurable variables and possible embodiments of the proposed invention

System Component	Current Prototype Configuration	Possible Variations or Extensions
Mobile chassis	Four-wheel-drive ground rover	Two-wheel-drive, tracked or other suitable mobile platforms
Movement control	ESP32 and L298N motor driver	Alternative embedded controllers and motor drivers
Steering	Differential steering	Configurable steering and navigation mechanisms
Robotic arm	Four-degree-of-freedom articulated arm	Alternative joint count, link lengths and actuator types
Servo control	PCA9685 PWM controller	Equivalent multi-channel servo controllers
Camera	ESP32-CAM with OV2640	Higher-resolution RGB, depth, thermal or multispectral cameras

Illumination	Camera-mounted or available inspection lighting	Adjustable LED and other suitable illumination arrangements
Environmental sensing	DHT11, capacitive moisture, rain, water-level and GPS modules	pH, NPK, electrical conductivity, leaf wetness, light, CO_2 and other sensors
Classification	EfficientNetV2-S	Other suitable CNN or transformer-based classifiers
Object detection	Modified YOLO26	Other suitable object detection architectures
Segmentation	Mobile-UNet	U-Net and other suitable segmentation models
Decision support	Random Forest and 12-rule risk engine	Additional machine learning models and configurable agronomic rules
Backend	Python, FastAPI and Docker Compose	Local, cloud-based or hybrid deployment
Communication	Configured Wi-Fi communication	Bluetooth, LoRa, cellular and other communication technologies
Voice interaction	XiaoZhi with English, Hindi and Punjabi support	Additional languages and supported voice service configurations
Computing	Backend-based inference	Onboard edge inference and hardware-optimised execution
Navigation	Operator-controlled movement	LiDAR-assisted mapping, localisation and autonomous navigation
Treatment	Advisory output only	Validated targeted application mechanism in a future embodiment
Power supply	Battery-based prototype arrangement	Solar-assisted and alternative rechargeable power configurations

G. WORKING PROTOTYPE/ FORMULATION/ DESIGN/COMPOSITION:

1. Prototype Availability

A working prototype of the AI-Powered Crop Intelligence Rover has been developed and assembled. It comprises a 4WD mobile chassis, four DC geared motors, an L298N motor driver, an ESP32 controller, a 4-DOF robotic arm, a PCA9685 servo controller, and an ESP32-CAM module with an OV2640 camera. It also includes environmental sensors for temperature, humidity, soil moisture, rainfall, and water-level monitoring, along with GPS-based positioning.

The prototype integrates the physical rover with a FastAPI backend, computer vision models, an environmental risk assessment engine, a crop recommendation model, a web dashboard, and a XiaoZhi voice assistant. Rover movement, robotic arm positioning, and camera-based inspection have been demonstrated through the browser-based interfaces.

Deployed dashboard:

https://aipoweredcropintelligencerover.dpdns.org

Local control interface:

agrirover.local

GitHub Repo:

https://github.com/MohammadFayasKhan/AIPoweredCropIntelligenceRover

2. Physical Rover and Integrated System Photographs



Fig. 9. Physical rover prototype showing the 4WD chassis, robotic arm, camera assembly and connected control interfaces.



Fig. 10. Rover positioned near a potted plant for close-range inspection using the mobile navigation interface.

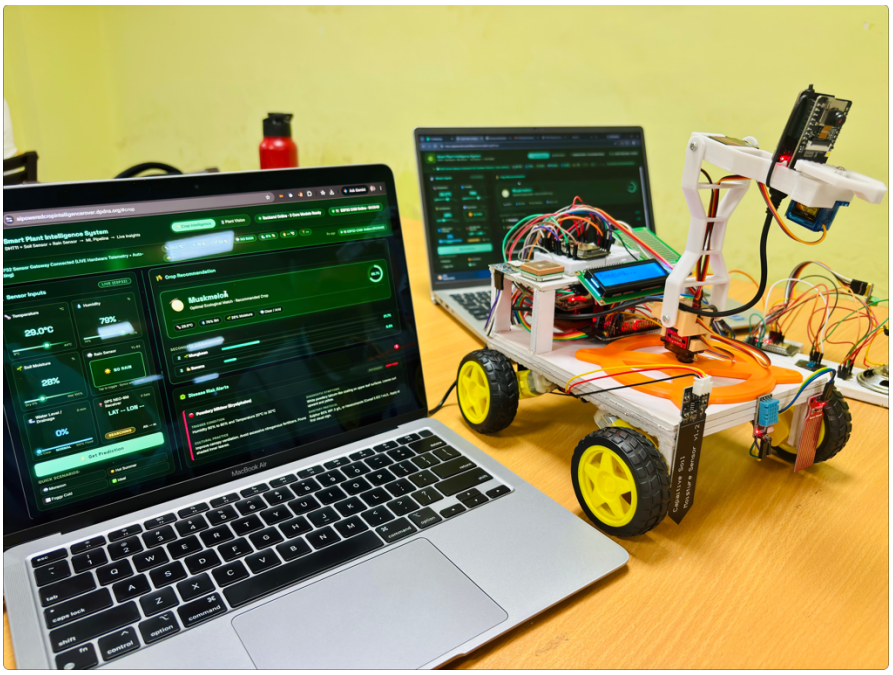


Fig. 11. Rover with the robotic arm positioned towards plant foliage and the dashboard displaying environmental data and crop recommendations.



Fig. 12. Crop inspection demonstration showing the rover, captured leaf image and plant vision interface.

3. Web-Based Environmental Monitoring and Crop Recommendation

The dashboard displays available environmental readings, including temperature, humidity, soil moisture, rain status, water level and GPS information. It also presents crop recommendations and environmental risk alerts.

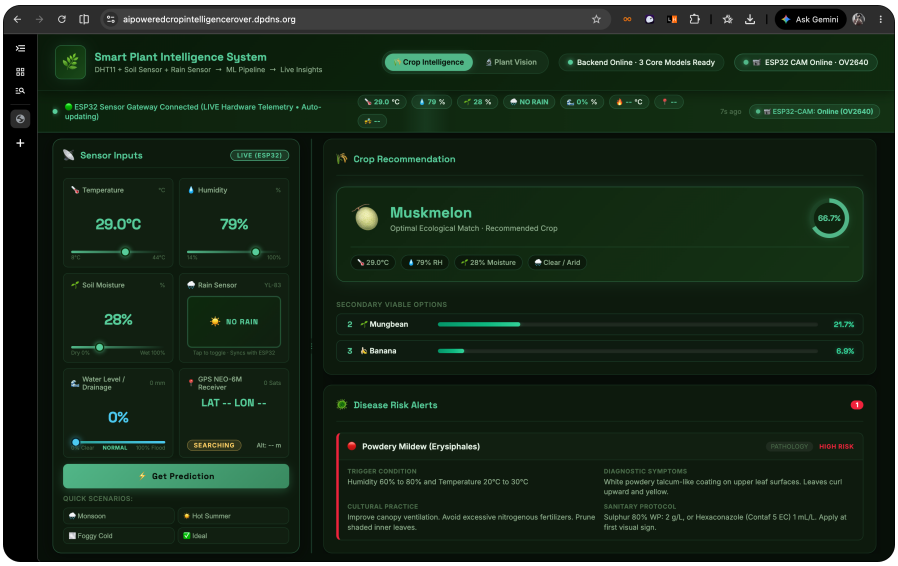


Fig. 13. Web dashboard displaying environmental telemetry, crop recommendations and risk assessment outputs.

4. Plant Disease Diagnosis Interface

The plant vision interface accepts submitted leaf images and displays the predicted category, confidence estimate, Grad-CAM visualisation, and available detection and segmentation outputs.

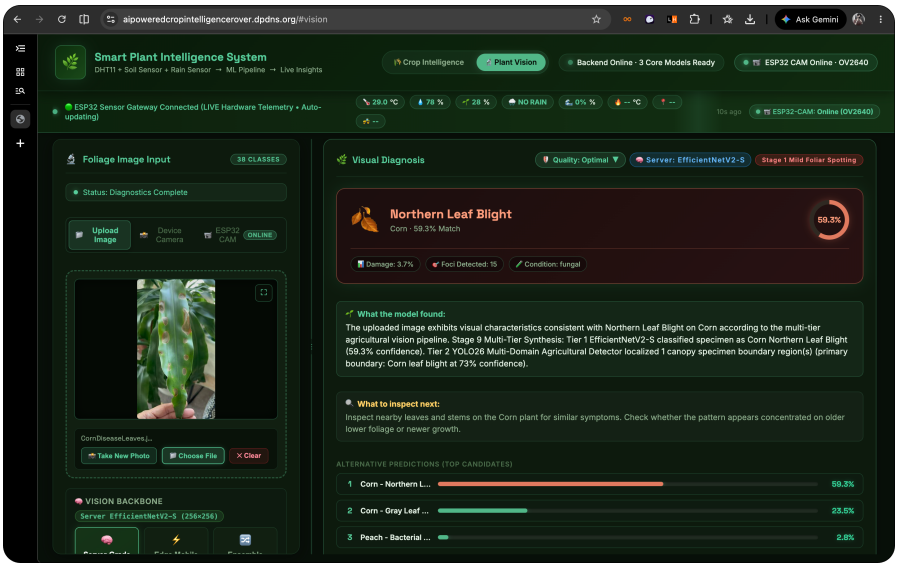


Fig. 14. Plant vision dashboard showing the submitted leaf image, EfficientNetV2-S classification, confidence estimate and visual analysis results.

5. Mobile Rover Navigation Interface

The mobile interface provides directional movement controls, speed settings, manoeuvre commands, and rover status information for operator-controlled navigation.

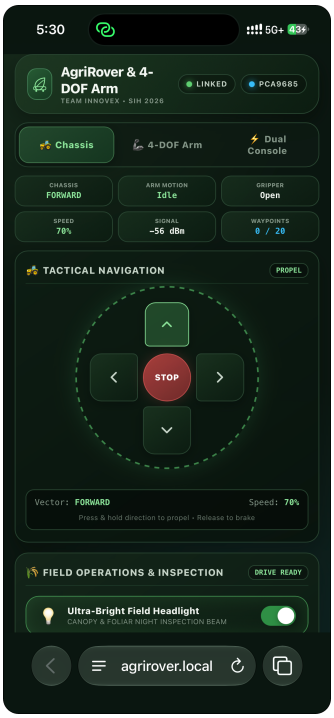


Fig. 15. Mobile teleoperation interface at agrirover.local, showing directional controls for rover movement

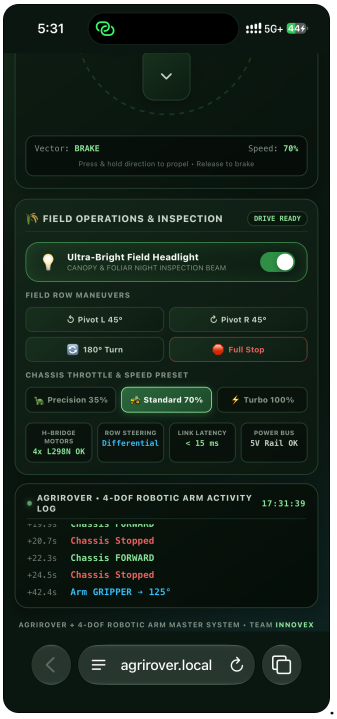


Fig. 16. Field operations console displaying manoeuvre controls, inspection-light settings, speed presets, and rover status

6. Robotic Arm Kinematics and Calibration Interface

The robotic arm interface provides joint controls for the base, shoulder, elbow, and gripper, together with calibration settings, movement speed adjustment, and positioning presets.



Fig. 17. Robotic arm interface showing the four-joint representation and commanded joint positions.



Fig. 18. Arm calibration interface displaying joint adjustment controls, movement settings, positioning presets, and waypoint-related controls.

7. XiaoZhi Voice Assistant Hardware and Operating States

The XiaoZhi assistant integrates an ESP32 controller, microphone, audio amplifier, speaker, and OLED display. The display indicates the assistant's current interaction state.

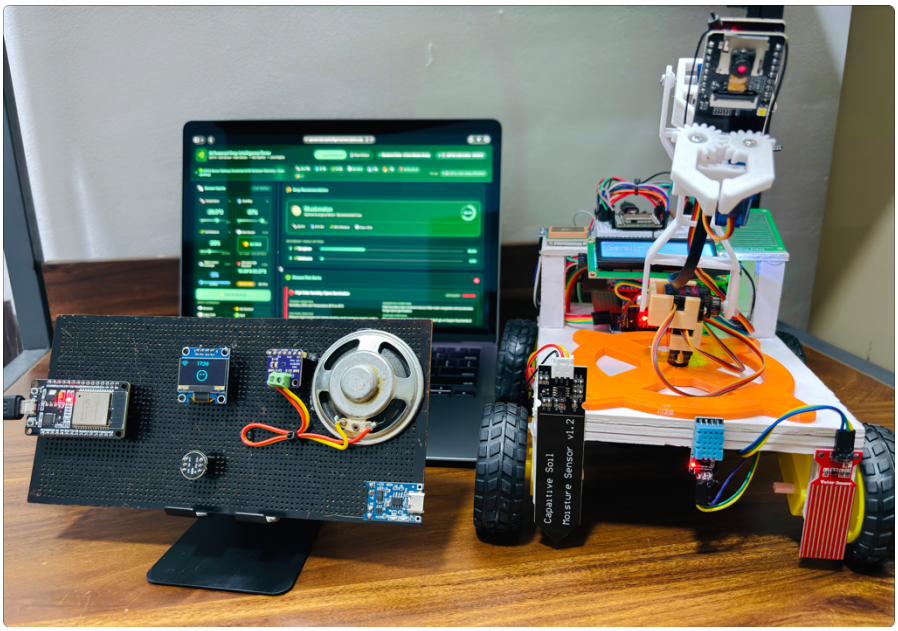


Fig. 19. XiaoZhi voice assistant hardware assembly in standby mode, integrated with the rover.

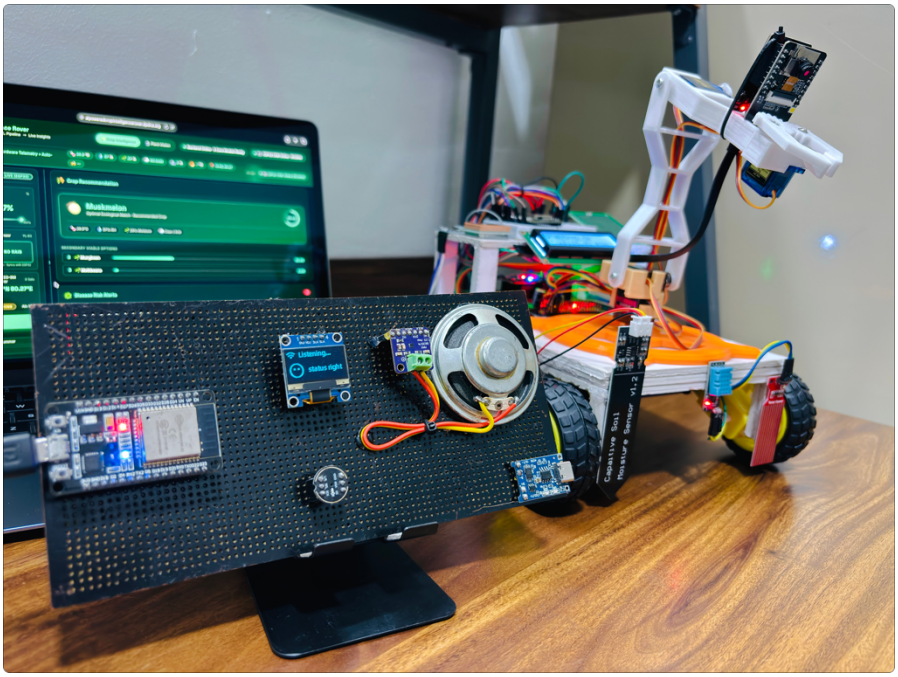


Fig. 20 XiaoZhi voice assistant displaying the listening state during spoken input.

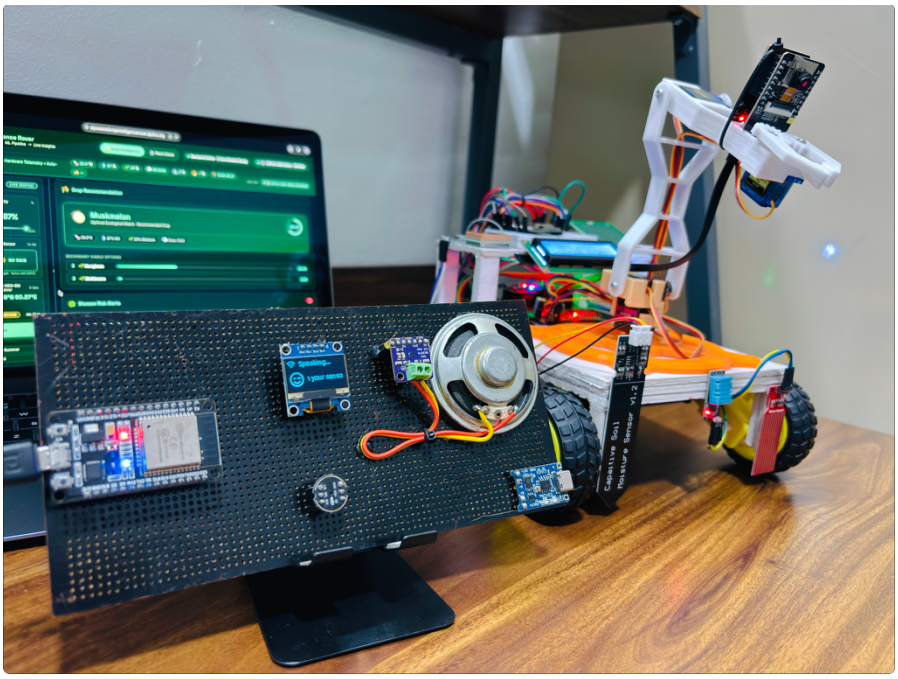


Fig. 21 XiaoZhi voice assistant displaying the speaking state during an audio response.

8. Prototype Demonstration Summary

The prototype photographs and software screenshots demonstrate the following implemented functions:

- Physical assembly and movement of the 4WD rover.
- Operator-controlled positioning of the 4-DOF robotic arm.
- Close-range image acquisition using the ESP32-CAM and OV2640 camera.
- Collection and display of environmental sensor readings.
- Presentation of crop recommendations and environmental risk alerts.
- Computer vision-based crop disease classification and available spatial analysis.
- Browser-based rover teleoperation and arm positioning.
- Voice interaction through the XiaoZhi assistant.

H. EXISTING DATA:

1. Available Experimental and Dataset Evidence

The invention is supported by agricultural image datasets, model evaluation results, environmental sensor readings, prototype demonstrations, and software interface outputs. These resources support the development and evaluation of image classification, object detection, lesion segmentation, and crop recommendation components.

Table VIII. Multi-source agricultural datasets and reported data partitioning

Dataset Source	Total Samples	Training	Validation	Testing	Target Task
PlantVillage	54,305	43,444	5,430	5,431	38-class disease classification
Field AI and PlantDoc field images	2,198	1,758	220	220	Field-image disease analysis
PlantDoc detection dataset	2,581	2,065	258	258	29-class object localisation
Agronomic crop profiles	2,200	1,760	220	220	22-class crop recommendation

The combined PlantVillage and field-image classification datasets contain 56,503 images. The datasets underwent preprocessing, including checks for duplicate and corrupted files, followed by an 80:10:10 training, validation, and testing split.

2. Existing Computer Vision Performance Data

The EfficientNetV2-S classifier achieved 95.13% test accuracy and a macro F1-score of 0.9354 across 38 classes, compared with 89.41% accuracy for the MobileNetV2 baseline.

Temperature scaling reduced the expected calibration error (ECE) from 0.1240 to 0.0803 using a fitted temperature of T = 1.42 and 15 confidence bins.

The modified YOLO26 detector achieved an mAP@50 of 0.3415, a precision of 0.3890, and a recall of 0.3650 on the PlantDoc detection task.

Mobile-UNet achieved a Dice score of 0.8420 and a mean intersection over union (IoU) of 0.7310, with 0.48 million parameters, a model size of 1.9 MB, and a GPU inference latency of 9.3 milliseconds per image.

The corresponding comparative tables are provided in Tables III, IV, and V of this disclosure.

3. Existing Crop Recommendation Data

The Crop_Recommendation.csv dataset contains 2,200 records across 22 crop classes, with seven features: nitrogen, phosphorus, potassium, temperature, relative humidity, soil pH, and rainfall.

The full-feature Random Forest model achieved 99.55% accuracy, while the reduced-feature configuration achieved 93.18% cross-validated accuracy using three selected inputs. These results represent separate configurations.

Since the physical rover does not directly measure all seven original features, the results must be interpreted according to the inputs and preprocessing used by each model. The corresponding crop recommendation comparison is provided in Table V.

4. Existing Environmental Monitoring Data

The prototype collects temperature, relative humidity, soil moisture, rainfall-related status, and water-level measurements through its connected sensors.

The dashboard presents available readings and outputs from the 12-rule environmental risk assessment engine. These outputs identify potential environmental risks but do not independently confirm plant diseases or predict crop damage.

5. Existing Prototype and Interface Evidence

The following figures provide evidence of the assembled prototype and its implemented functions:

- **Figures 9-12:** Physical rover, robotic arm, camera positioning, and close-range plant inspection.
- **Figures 13-14:** Environmental monitoring, crop recommendation, and plant disease analysis dashboards.
- **Figures 15-18:** Browser-based rover navigation and robotic arm control interfaces.
- **Figures 19-21:** XiaoZhi voice assistant hardware and its standby, listening, and speaking states.

These photographs and screenshots demonstrate the integration of the physical hardware, backend processing, and user interfaces.

6. Comparative Evidence and Technical Limitations

The project includes comparative results for disease classification, confidence calibration, object detection, lesion segmentation, and crop recommendation. Each metric evaluates a different performance characteristic and should be interpreted independently.

The available results demonstrate individual model performance and prototype-level integration. Further evaluation is required across different crop species, locations, seasons, lighting conditions, soil types, and field environments.

7. Field Validation and Additional Data Requirements

The current prototype has not been evaluated through large-scale controlled field trials across multiple farms or growing seasons. Verified measurements of crop-yield improvements, irrigation-water savings, pesticide reduction, and fertiliser reduction are also unavailable.

Further validation should include:

- Outdoor trials across different crops and field conditions.
- Evaluation using independent field-collected images.
- Comparison of disease predictions with expert-verified diagnoses.
- Sensor calibration against reference instruments.
- Crop recommendation evaluation using verified soil and environmental measurements.
- Validation of environmental risk rules against agronomic observations.

- Testing of rover movement, arm-position repeatability, and image acquisition under field conditions.

No clinical data are applicable to this agricultural invention. Its supporting evidence consists of agricultural datasets, model evaluation metrics, environmental measurements, prototype demonstrations, and comparative technical results.

The available evidence establishes the technical development and integration of the AI-Powered Crop Intelligence Rover as an agricultural inspection and decision-support prototype. Further independent field validation is required to establish large-scale effectiveness and measurable agricultural benefits.

4. USE AND DISCLOSURE (IMPORTANT):

A. Have you described or shown your invention/ design to anyone or in any conference?	YES ( )	NO (✓)
B. Have you made any attempts to commercialize your invention (for example, have you approached any companies about purchasing or manufacturing your invention)?	YES ( )	NO (✓)
C. Has your invention been described in any printed publication, or any other form of media, such as the Internet?	YES ( )	NO (✓)
D. Do you have any collaboration with any other institute or organization on the same? Provide name and other details.	YES ( )	NO (✓)
E. Name of Regulatory body or any other approvals if required.	YES ( )	NO (✓)

5. PUBLIC DISCLOSURE LINKS:

The invention titled “AI-Powered Crop Intelligence Rover” has not been formally disclosed through journal publications, conference papers, published research articles, or patent applications.

The project includes supporting online resources containing source code, a deployed application, demonstration materials, and technical documentation. These resources are listed separately at the end of this document.

6. MOU / COLLABORATION TERMS:

Not applicable. The invention has been developed as an academic project at Lovely Professional University through team-based technical development and academic guidance. No external memoranda of understanding (MOUs), industrial collaboration agreements, sponsored research

contracts, joint-development agreements, or technology-transfer arrangements have been established in relation to this invention.

Any future academic, industrial, or commercialisation partnerships will be governed by separate agreements, subject to applicable university intellectual property policies and ownership requirements.

7. POTENTIAL FOR COMMERCIALISATION:

The AI-Powered Crop Intelligence Rover can be commercialised in precision agriculture, agricultural robotics, crop monitoring and digital farming. It combines mobile inspection, artificial intelligence, IoT-based environmental sensing and decision support in one platform for monitoring plant health and supporting crop-related decisions.

Market Opportunity

Farms and agricultural institutions need practical ways to inspect crops, analyse plant diseases and monitor environmental conditions. The growing use of artificial intelligence, IoT sensors and agricultural robotics creates room for integrated monitoring solutions. The invention responds with a ground-based mobile rover that captures close-range plant images, analyses visible symptoms, monitors environmental conditions and recommends suitable crops. Its modular design allows adaptation to agricultural fields, greenhouses, polyhouses, nurseries and agricultural research facilities.

Competitive Differentiation

Existing agricultural monitoring systems usually handle a single function, such as environmental sensing, aerial imaging or disease classification. This invention is differentiated by combining the following in one system:

- Four-wheel-drive mobile agricultural inspection.
- Adjustable camera positioning through a 4-DOF robotic arm.
- Close-range plant image acquisition using ESP32-CAM.
- AI-based disease classification and confidence calibration.
- Grad-CAM visualisation and symptom localisation.
- Pixel-level lesion segmentation using Mobile-UNet.
- Multi-parameter environmental monitoring.
- Rule-based environmental risk assessment.
- Random Forest-based crop recommendation across 22 crop classes.
- Browser-based rover control and monitoring.
- Multilingual voice assistance in English, Hindi and Punjabi.

Because these functions share one platform, plant-health analysis and environmental information can be read side by side.

Social and Environmental Impact

In addition to its commercial potential, the invention may contribute to agricultural development by:

- Supporting systematic crop inspection and plant-health monitoring.
- Assisting in the identification of visible plant symptoms.
- Providing environmental risk alerts and crop recommendations.
- Improving access to agricultural information through multilingual voice interaction.
- Supporting informed crop-planning and monitoring decisions.
- Encouraging the adoption of accessible agricultural robotics and IoT technologies.

Commercial Assessment

The invention has progressed beyond conceptual development and includes a working physical prototype with integrated hardware, computer vision models, environmental monitoring, crop recommendation, backend processing, and user interfaces.

Possible commercialisation routes are agricultural rover sales, software subscriptions, crop-inspection services, technology licensing and institutional deployment. Before large-scale deployment, the invention still needs further field validation, product refinement, a manufacturing-cost assessment and a market evaluation.

8. TARGET COMPANIES FOR COMMERCIALISATION:

The organisations below are potential commercialisation or collaboration partners because of their work in agricultural machinery, precision farming, agricultural AI, IoT monitoring or crop-health management.

Company	Relevance	Strategic Fit
John Deere India	Precision Agriculture	Pairs ground-based crop inspection with agricultural machinery, precision farming and digital agriculture platforms.
Trimble Agriculture	Farm Management Technology	Feeds crop-monitoring information into precision agriculture and field analytics solution.
Bayer Crop Science	Agricultural Technology and Crop Science	Possible collaboration on digital crop monitoring, plant-health analysis and agricultural decision-support applications.
Corteva Agriscience	Seeds and Agronomy	Use of plant-health monitoring and crop inspection technologies in agricultural research and crop trials.
Cropin Technology	AI in Agriculture	Adds computer vision outputs and environmental information to agricultural intelligence and farm analytics platforms.
AgNext Technologies	Agricultural Analytics	Possible collaboration on agricultural AI, image analysis and technical validation.

Mahindra & Mahindra	Farm Equipment and Mechanisation	Mechanical platform development, rover manufacturing, integration with agricultural equipment and field trials.
TAFE	Agricultural Machinery	Possible development of mechanical platforms and integration with agricultural equipment.
Fasal	IoT-Based Precision Agriculture	Adds environmental sensing and crop-risk assessment to agricultural monitoring information.
BharatRohan	Aerial Crop Monitoring	Ground-level crop inspection to complement aerial agricultural monitoring.
Marut Drones	Agricultural Robotics and Drones	Possible integration of ground-based inspection with agricultural monitoring technologies.
DeHaat	Agricultural Services and Farmer Advisory	Possible pilot deployment through agricultural service networks and farmer-oriented monitoring services.

9. DEPENDENCY ON EXISTING PATENTS

The development of the AI-Powered Crop Intelligence Rover did not identify any direct dependency on a specific third-party patent or patent licensing agreement. The invention builds on established technologies and commercially available hardware: embedded controllers, servo control modules, wireless communication interfaces, machine learning architectures and computer vision methods. In this system these are ESP32 controllers, PCA9685 servo control, EfficientNetV2-S, temperature scaling, Grad-CAM, YOLO26, Mobile-UNet, Random Forest and a FastAPI-based backend. The technical contribution of the invention is the coordinated integration of these components into a single mobile agricultural inspection and decision-support platform. In particular, the system combines:

- Ground-based mobile crop inspection
- Adjustable robotic camera-positioning mechanism
- Close-range plant image acquisition
- Multi-stage computer vision-based crop disease analysis
- Environmental sensing and risk assessment
- Machine learning-based crop recommendation
- Integrated backend processing and browser-based monitoring
- Multilingual voice-based access to agricultural information

No specific third-party patent royalty or licensing obligation has been identified in the development of the proposed invention.

10. FILING OPTIONS:

The AI-Powered Crop Intelligence Rover is ready for a Provisional Patent Filing, with its working prototype and supporting technical documentation providing a foundation for securing an initial priority date while allowing further refinement and field validation.

11. KEYWORDS:

Category	Keywords
Agricultural Robotics	AI-Powered Crop Intelligence Rover; Agricultural Inspection Robot; Smart Agriculture; Precision Farming; Ground-Based Crop Monitoring; Mobile Agricultural Robotics
Robotic Hardware	Four-Wheel-Drive Agricultural Rover; Four-Degree-of-Freedom Robotic Arm; Articulated Robotic Manipulator; Adjustable Camera Positioning; ESP32-CAM; Robotic Teleoperation
IoT and Environmental Monitoring	Internet of Things (IoT); Environmental Sensor Integration; Soil Moisture Monitoring; Temperature and Humidity Monitoring; Rainfall Monitoring; Water-Level Monitoring; GPS-Based Field Monitoring
Artificial Intelligence and Computer Vision	Plant Disease Classification; EfficientNetV2-S; Temperature Scaling; Confidence Calibration; Grad-CAM; YOLO26 Object Detection; Plant Symptom Localisation; Mobile-UNet Segmentation; Affected Leaf Area Estimation
Agricultural Decision Support	Environmental Risk Assessment; Rule-Based Agronomic Analysis; Random Forest Crop Recommendation; Crop Suitability Prediction; Agricultural Monitoring
Software and Communication	FastAPI Backend; Edge-to-Cloud Architecture; Web-Based Agricultural Dashboard; Mobile Robotic Teleoperation; Multilingual Agricultural Voice Assistant; Model Context Protocol (MCP); Integrated Agricultural Decision-Support System

PROJECT LINKS AND SUPPORTING RESOURCES

1. GitHub Source Repository https://github.com/MohammadFayasKhan/AIPoweredCropIntelligenceRover	**2. Deployed Cloud Web App** https://aipoweredcropintelligencerover.dpdns.org
3. YouTube Demonstration Video https://youtu.be/BdzizjHH6jI	**4. Google Drive Project Archive** https://drive.google.com/drive/folders/16rCbgLONgS9XceWDxLdKzxy1fksVcTtO?usp=sharing