



AgriRover Pro: Intelligent Autonomous Farming Robot Using IoT and Computer Vision: A Review

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Abstract. Farming includes many activities such as checking soil, watering plants, sowing seeds, observing crop growth, and avoiding damage to plants. These activities often need regular visits to the field and a lot of manual work. This review studies three research papers about agricultural rovers and smart farming. The first paper describes a rover that combines several farm tasks, including irrigation, spraying, seed sowing, obstacle detection, and wireless monitoring [1]. The second paper presents a low-cost autonomous Agri-Rover that uses an ESP32 controller, sensors, motors, and an IoT connection for tasks such as sowing and environmental monitoring [2]. The third paper presents a crop-monitoring robot that uses a camera, Raspberry Pi, ESP32, and a CNN-based image model to identify fruits and vegetables and collect soil information [3]. The papers show that sensors, cameras, mobile robots, and wireless communication can be used together to support farm work. They also show that field conditions, battery life, navigation, image accuracy, cost, and network coverage are important issues. Based on these papers, this review presents AgriRover Pro as a proposed student-level design that combines IoT monitoring with camera-based crop observation. The proposed system has not yet been built or tested, so its performance must be checked through future experiments.

Keywords: AgriRover Pro, Autonomous Farming Robot, Smart Agriculture, Internet of Things (IoT), Computer Vision, Precision Agriculture, Agricultural Robotics, Artificial Intelligence (AI), Machine Learning, Real-Time Crop Monitoring, Automated Weed Detection, Obstacle Avoidance, Smart Farming, Sensor Integration, Sustainable Agriculture, Agricultural Automation, Deep Learning, Crop Health Monitoring.

I. Introduction

Agriculture is an important part of daily life because it provides food and work for many people. Farmers have to complete different activities at the right time. These activities may include checking the soil, watering crops, sowing seeds, spraying when needed, and watching for crop problems. On a large farm, checking every part of the field can take a long time. Some tasks also need repeated physical effort.

Technology can support farmers by collecting information and helping with repeated jobs. A sensor can measure a condition such as soil moisture. A camera can take pictures of plants. A controller can read the sensor values and control motors or a pump. IoT can send selected readings to a phone or computer. A rover brings these parts together on a moving platform, so it can visit different points in a field rather than staying in one place.



The term smart farming is used when digital tools are used to support farm decisions and activities. It does not mean that every job is done without a person. In many student projects, the robot performs a small number of clearly defined tasks and the farmer or operator still checks the results. This is a sensible starting point because outdoor farming is not a controlled laboratory environment. Soil may be dry, loose, muddy, or uneven. Sunlight changes during the day, and plants may cover sensors or camera views.

A mobile agricultural robot can be useful because it can carry sensors to different locations. For example, a soil-moisture sensor can take readings at selected points rather than relying on a single measurement from the edge of a field. A camera can collect pictures from close to the plants. If the rover is connected to an IoT dashboard, the readings can be viewed later and compared. However, the readings must be checked for errors, and the camera model must be tested on the crops and conditions where it will be used.

The three supplied research papers focus on different parts of this idea. Bhirud and colleagues describe a multi-tasking rover for irrigation and other field operations [1]. Venkatesan and colleagues focus on a low-cost rover with an ESP32, motors, sensors, and sowing-related mechanisms [2]. Sudha and colleagues study a robot that combines image recognition, soil-moisture sensing, and obstacle avoidance [3]. Reading the papers together helps identify which features may be useful in one combined student project.

1. Aim of the Review

The aim of this review is to understand the three research papers and use their ideas to describe a possible design for AgriRover Pro. The review does not claim that the proposed robot has already been built or that it has achieved the results reported by the original authors.

2. Objectives

- To explain the main idea and working method of each supplied research paper.
- To compare the hardware, sensors, communication methods, and farming tasks described in the papers.
- To understand how IoT and computer vision can support different farm activities.
- To identify practical problems such as image errors, uneven soil, power limits, and communication loss.
- To suggest a simple conceptual design and a future testing plan for AgriRover Pro.

3. Scope

This review focuses on mobile ground robots, sensors, crop images, IoT communication, and selected farm tasks. It discusses only the three research papers supplied for this assignment. The design suggestions for AgriRover Pro are based on the features discussed in those papers and are presented as a proposal for further student work.

II. Review Methodology

The three supplied research papers were read to understand their aim, design, main components, working method, reported results, limitations, and future suggestions. The first paper is “Smart Agriculture Rover with Multi Tasking Mechanism” [1]. The second is “Design of Low Cost Autonomous Agri-Rover System with Automated Farming Applications” [2]. The third is “AI-Enabled Autonomous Agricultural Monitoring Robot for Precision Farming Using CNN and IoT” [3]. The comparison is a focused narrative review, not a complete survey of every paper on agricultural robots.

Information from each paper was grouped into common topics: movement and farm operations, sensor use, IoT communication, camera-based crop checking, power and cost, and problems reported by the authors. The results from the papers are kept



separate because the robots use different components and were tested in different conditions. A value reported by one research team should not be treated as a measured result for AgriRover Pro.

III. Basic Technologies Used in Smart Farming

1. Agricultural Rover

An agricultural rover is a small mobile robot designed to move through a field. A basic rover usually has a frame, wheels, motors, a motor driver, a battery, and a controller. Extra tools can be attached for activities such as sowing or watering. The frame should be strong enough to carry the components, but the robot should not be so heavy that it sinks into soft soil. Wheel size, ground clearance, turning space, and the distance between crop rows affect movement.

2. Sensors

Sensors measure conditions that the controller cannot know by itself. A soil-moisture sensor gives an estimate of how wet the soil is at its position. A temperature-and-humidity sensor measures the surrounding air conditions. An ultrasonic sensor sends a sound pulse and measures its return time to estimate the distance to an object. These readings can help the rover decide when to stop or when to show a warning. Sensors need correct placement and calibration because incorrect readings can lead to incorrect actions.

3. Internet of Things (IoT)

IoT connects physical devices to a network so that information can be viewed or stored remotely. A microcontroller such as ESP32 can send readings through Wi-Fi when a suitable network is available. A dashboard may show sensor values, battery status, and recent alerts. The internet connection should not be the only safety method: obstacle stopping and emergency control should continue locally if the network is lost.

4. Computer Vision

Computer vision means using a camera and computer software to understand information in images. A model can be trained to recognise selected objects or plant features. In the third supplied paper, a CNN-based model is used for fruit and vegetable identification [3]. Image results can be affected by light, background, camera position, and the number of training images. A model's prediction should therefore be treated as an estimate until it has been tested in real field conditions.

IV. Literature Review

1. Smart Agriculture Rover with Multi Tasking Mechanism [1]

The first research paper describes a smart rover intended to help with more than one farm activity. The paper discusses automatic irrigation, environmental sensing, obstacle detection, and manual control through a wireless connection. It describes a mobile platform that carries the drive system, controller, sensors, pump, and related electrical parts. The purpose is to bring several functions into one device instead of using a separate setup for every task.

One important part of the system is soil-moisture-based irrigation. The sensor checks the moisture level and the controller compares it with a chosen limit. When the soil is below the selected limit, the pump can be switched on through a relay. When enough moisture is detected, the pump can be switched off. This type of control can help avoid running a pump continuously when watering is not required. The paper also discusses temperature and humidity readings, which can be recorded to understand the local conditions.

The paper describes a rover based on common low-cost parts, including a controller, motor driver, geared motors, moisture sensor, DHT11 sensor, relay, pump, battery, and wireless communication module. Manual control is useful when the operator



needs to move the rover to a particular location or check a problem. Automatic operation can handle a defined task after the threshold and control rules have been set.

2. Main Contributions

It brings mobility, sensor readings, and irrigation control into one platform. It uses soil moisture as a simple input for deciding when watering is needed. It includes a manual control option, which is useful when automatic operation is not suitable. It uses widely available electronic parts that can be studied and assembled in a student laboratory. It discusses possible future additions such as solar power, IoT dashboards, and AI-based crop analysis.

3. Limitations and Points to Consider

The paper is mainly focused on rover movement, sensing, and farm operations. It does not provide a detailed crop-image recognition system as its main feature. A moisture sensor also measures only the soil close to its probe; it cannot automatically describe the moisture level of the entire field. The selected threshold may need to change with crop type, soil type, plant age, and weather. Pump control must be tested carefully so that it does not cause overwatering or run dry.

The paper gives a useful example of how basic electronics can automate a repeated job. For AgriRover Pro, this idea can be combined with camera-based crop observation. The design should keep the watering function separate from the image-recognition function so that an image prediction does not directly activate a pump unless a safe and tested rule has been defined.

4. Relevance to AgriRover Pro

This paper is most useful for the movement and task-control part of the proposed system. Its moisture-based pump logic and manual override are simple ideas that a student team can understand and test. The main lesson is that automation should have clear rules, safe stopping, and a way for the user to take control.

5. Results Reported by the Authors

The authors report an average movement speed of about 0.65 m/s, obstacle-detection accuracy of around 94% within a stated distance range of 5–150 cm, seed spacing accuracy of about ± 2.5 cm, and average IoT dashboard response time of approximately 2.1 seconds. They also report around 3.8 hours of operation under mixed conditions. These values are reported by the authors for their system; they should not be presented as expected results for AgriRover Pro without repeating the tests.

6. Strengths

The design gives attention to cost and the use of commonly available components. It includes both manual and automatic modes. It covers more than one farm activity, including seed sowing and environmental monitoring. It gives measurable results for movement, obstacle detection, seed spacing, dashboard response, and operation time. It identifies future additions such as GPS, solar charging, and crop-image analysis.

7. Limitations

The authors note that movement becomes less accurate in muddy or waterlogged soil and that battery capacity limits long working periods. An ultrasonic sensor can detect nearby obstacles but cannot by itself provide accurate navigation across a large field. Wi-Fi or Bluetooth performance also depends on distance and interference. The paper's reported values were obtained under its test conditions and may be different in another farm, with another crop or a different rover weight.

8. Relevance to AgriRover Pro

This paper is useful for selecting a low-cost controller, drive motors, sensor set, and basic navigation method. It also shows why the proposed system needs a practical test plan. For AgriRover Pro, the same general design could be used as a starting point, while the camera and image-processing part would need to be added and tested separately.

**AI-Enabled Autonomous Agricultural Monitoring Robot for Precision Farming Using CNN and IoT [3]**

The third paper, by Sudha and colleagues, focuses on monitoring crops and field conditions by combining a camera, sensors, and a mobile robot. It uses a Raspberry Pi for image processing and higher-level decisions, while an ESP32 supports motor control and related functions. A camera captures pictures, and a CNN-based model is used to identify selected fruits and vegetables. The robot also measures soil moisture and uses an ultrasonic sensor to help avoid obstacles. An LCD screen displays the results and selected environmental information.

A CNN, or convolutional neural network, is a type of computer model that learns patterns from images. During training, the model is shown labelled images. Later, it uses learned patterns to make a prediction about a new image. The quality of the result depends on the images used for training and testing. If the test images are very different from the training images, the model may make mistakes. For example, low light, shadows, overlapping leaves, different camera angles, and a busy background can make an object harder to recognise.

1. Results Reported by the Authors

The paper reports average image-classification accuracy of about 70%, a response time of approximately 1–3 seconds, and obstacle-avoidance performance of around 90%. The authors describe the system as able to identify examples such as carrots, bananas, and apples, while also displaying sensor information. The paper recognises that image-classification accuracy can be improved by using a larger and more varied dataset and by testing improved models.

2. Limitations

The reported classification accuracy of about 70% shows that image recognition is not perfect. The result may change when the camera is used outdoors with different light, crop stages, or backgrounds. Identifying a fruit or vegetable is also different from detecting a plant disease. A disease-detection feature would need a suitable dataset, clear labels, and review by agricultural experts. The system should not be treated as a replacement for a farmer's judgement.

3. Relevance to AgriRover Pro

This paper gives the main idea for the computer-vision part of AgriRover Pro. A camera and a small computer could be used to capture images and classify selected crop-related objects. The results could be shown alongside sensor readings on a dashboard.

V. Comparative Analysis of the Three Papers

The three papers share a common goal: using a moving robot and electronic components to make some farm tasks easier. However, each paper gives more attention to a different part of the problem. The first paper concentrates on combining farm tasks and irrigation control [1]. The second focuses on a low-cost rover and reports measurements for movement, seed spacing, obstacle detection, and IoT response [2]. The third gives more attention to image recognition and crop monitoring [3].

• Feature	• Paper 1: Multi-tasking rover [1]	• Paper 2: Low-cost Agri-Rover [2]	• Paper 3: AI monitoring robot [3]
• Main focus	• Several farm tasks and irrigation	• Low-cost movement, sowing, monitoring	• Crop images and sensor monitoring
• Controller / computing	• Embedded controller; rover control	• ESP32 and motor-control electronics	• Raspberry Pi for images; ESP32 for control



• Sensors	• Soil moisture, temperature/humidity, obstacle sensing	• DHT11, ultrasonic and related sensors	• Soil moisture and ultrasonic sensing; camera
• Camera / AI	• Not the main feature	• Suggested as a possible extension	• CNN-based fruit and vegetable recognition
• Communication	• Wireless/manual control; future IoT additions discussed	• Wi-Fi/Bluetooth and IoT dashboard	• Sensor and image results displayed; IoT integration
• Reported measures	• Discusses operating functions and energy/resource benefits	• 0.65 m/s; ~94% obstacle detection; ± 2.5 cm seed spacing; ~2.1 s dashboard response; ~3.8 h operation	• ~70% image classification; 1–3 s response; ~90% obstacle avoidance
• Main concern	• More detailed crop-image analysis needed	• Performance on muddy soil and battery limits	• Image accuracy and changing outdoor conditions
• Useful idea for AgriRover Pro	• Task control and moisture-based irrigation	• Affordable rover base and sensor integration	• Camera-based crop checking and display

1. What the Comparison Shows

The comparison suggests that a useful student project does not need to copy every feature from all three systems. It is better to choose a small set of functions and make them work reliably. A possible first version could move slowly, detect nearby obstacles, collect soil-moisture readings, capture crop pictures, and send information to a dashboard. A watering tool or seed dispenser could be added after the basic movement and monitoring functions have been tested.

The reported results should not be compared as if the papers used the same test setup. One paper reports seed spacing and dashboard response, while another reports image-classification accuracy. These measures describe different tasks. To compare systems fairly, a future experiment would need the same field, crop, test distance, lighting, measurement method, and number of repeated trials.

2. Main Lessons from the Papers

Low-cost parts can support a student prototype, but wiring, battery capacity, and mechanical strength still need attention.

Sensor readings and camera predictions provide different types of information; they should be shown separately and combined only when a clear rule is available.

Automatic operation should include manual override, obstacle stopping, and a safe response to low battery or sensor failure.

Performance values should be reported with the conditions in which they were measured.

Field testing is necessary because laboratory or limited demonstrations cannot represent every type of soil and weather.

VI. Proposed AgriRover Pro System

AgriRover Pro is proposed as a student-level mobile robot that combines basic farm sensing, camera-based crop observation, and IoT monitoring. The purpose is to connect useful ideas from the three reviewed papers in one design. This section explains a possible design, not a completed or experimentally tested product.



1. Proposed Main Components

— Part	— Possible choice	— Purpose
— Mobile base	— Small rover chassis with geared DC motors	— Move through a selected crop row
— Main controller	— ESP32 or similar microcontroller	— Read sensors and control motors
— Image-processing unit	— Raspberry Pi-class board or equivalent	— Process images from the camera
— Camera	— RGB camera module	— Capture crop and field pictures
— Soil sensor	— Soil-moisture sensor	— Measure moisture near the probe
— Environment sensor	— Temperature/humidity sensor	— Record surrounding conditions
— Obstacle sensor	— Ultrasonic distance sensor	— Detect nearby objects
— Motor driver	— Suitable dual H-bridge driver	— Supply motor current and control direction
— Communication	— Wi-Fi / IoT dashboard	— Send readings and show robot status
— Power	— Rechargeable battery and voltage regulators	— Power the motors and electronics

2. Simple System Architecture

FIELD INPUTS: Camera images • Soil moisture • Temperature / humidity • Obstacle distance
DATA COLLECTION: ESP32 reads sensors and motor status; camera sends images to the processing unit
PROCESSING AND DECISION: Image model checks selected classes; control rules check sensor values and safety
OUTPUTS: Motor movement • Local stop/turn • Optional tested watering action • IoT dashboard / LCD

3. Proposed Working Steps

- The operator switches on the rover and checks the battery, sensors, camera, and emergency stop.
- The rover moves slowly through a short crop row. The distance sensor checks for nearby objects.
- If an object is too close, the rover stops and waits or turns only if the programmed safety rule allows it.
- The camera captures a picture at a selected interval. The image-processing unit predicts the selected object class.
- The controller records soil-moisture and environmental readings with a time label.
- The rover sends readings and image results to the dashboard when the network is available.
- If a watering unit is added, it follows a separately tested moisture threshold and can be stopped manually.
- The system stores readings locally or stops safely if communication fails, the battery becomes low, or a sensor reports an error.

VII. Integration Issues and Research Gaps

The three papers show that individual functions can be developed with affordable components. Combining them into one reliable robot is a separate challenge. A rover must carry the camera and sensors without blocking their view. The motors create vibration, which can blur images. The controller must handle movement and safety while the image-processing unit may need more time to analyse a picture. The system should not wait for an image prediction before stopping for a close obstacle.

1. Camera and Image-Recognition Problems

The third paper reports around 70% average classification accuracy [3]. This is useful evidence that the model can identify some images, but it also means that some predictions may be wrong. For a student project, the first step should be to choose a small set of target classes, collect different images, and keep separate training and testing images. Images should include



different light levels, angles, backgrounds, and crop stages. Similar or repeated images should not appear in both training and test sets because that can make the test result look better than it really is.

The robot should save low-confidence predictions for review rather than automatically taking an action. A fruit or vegetable classifier should not be described as a disease detector unless the model has been trained and tested for disease classes. If disease screening is added later, agricultural experts should review the labels and recommendations.

2. Navigation and Outdoor Movement

Ultrasonic sensors are useful for detecting nearby objects, but they do not tell the rover its exact location in a large field. Wheels can slip on wet soil, and plants may hide objects from the sensor. GPS, wheel encoders, an inertial sensor, or camera-based row following may improve navigation, but each option adds cost and development work. A first prototype should operate at low speed on a small test path, with a human operator nearby and an easy way to stop it.

3. Power and Mechanical Design

The battery must supply current to the motors and any pump, camera, controller, and communication module. A pump or motor starting suddenly can cause a voltage drop and reset the electronics. Separate regulated supplies, suitable wiring, fuses, and a measured battery test can help. The frame should protect wiring from dust and moisture. The robot should be light enough for the selected soil but strong enough to carry its parts.

4. IoT and Communication

A dashboard is useful only when the data are clear and timely. The display should show the measurement, unit, time, and connection status. If Wi-Fi is lost, local movement safety should continue. Readings can be stored temporarily and uploaded later. The project should avoid sending passwords in public code and should limit access to controls.

5. Main Research Gaps

Few of the reviewed functions are measured together using one common test procedure. Image recognition needs testing across crops, lighting, backgrounds, and field conditions. Obstacle detection and whole-field navigation are different problems and need separate evaluation. Battery runtime and total cost should be measured with the final robot and tools attached. Safe behaviour during weak internet, sensor errors, low battery, or uncertain predictions must be planned.



VIII. Suggested Testing and Evaluation Plan

Before claiming that AgriRover Pro is useful, the team should test each function separately and then test the combined system. The testing process should record what was tested, where it was tested, the number of trials, and any failure. The team should report actual measurements rather than copying performance numbers from the reviewed papers.

Test area	How to test	What to record
Movement	Run the rover along a marked short path several times	Distance travelled, time, route errors, number of stops
Obstacle detection	Place safe obstacles at known distances	Correct detections, missed detections, stopping distance
Soil moisture	Compare sensor readings with repeated measurements at selected points	Raw reading, calibrated value, variation between trials
Image model	Use separate test images not used during training	Correct and incorrect predictions by class, accuracy, precision/recall if calculated
IoT dashboard	Send readings at a fixed interval and interrupt Wi-Fi during a test	Delay, missing messages, reconnection and data recovery
Battery	Operate the complete rover under a repeatable workload	Runtime, battery voltage, resets, load conditions
Safety	Test emergency stop and low-battery response under supervision	Whether the rover stops as expected and how long it takes
Cost	Record all components and fabrication expenses	Total prototype cost and maintenance items

1. Fair Reporting of Results

Image classification accuracy can be calculated as the number of correct predictions divided by the total number of test predictions, multiplied by 100. However, one overall percentage may hide weak performance on a particular class. The report should also show how many examples were tested for each class. For obstacle detection, the number of missed obstacles is important, because a missed obstacle may be more serious than a false alarm. The rover's speed and stopping distance should be measured on the same surface when comparing repeated runs.

2. Future Scope

After a basic version works, the project could be improved in stages. GPS or another positioning method could help record where readings were collected. A better camera dataset could improve recognition of selected crops. A row-following method could make movement more consistent. Solar charging may be tested if the battery and power needs are understood. A removable tool could support seed sowing or watering, but each tool should be tested separately before being used with the automatic navigation system.

IX. Conclusion

This review studied three research papers about agricultural rovers, IoT, and camera-based crop monitoring. The first paper shows how one rover can support several farming tasks and use soil-moisture readings to control irrigation [1]. The second paper describes a low-cost rover using an ESP32, motors, sensors, and wireless communication, and reports measurements for movement, seed spacing, obstacle detection, dashboard response, and operating time [2]. The third paper combines a camera, Raspberry Pi, ESP32, soil sensing, obstacle avoidance, and a CNN model for recognising selected fruits and vegetables [3]. The main point from the review is that IoT and computer vision provide different but useful information. Sensors give measurements about the field, while a camera provides pictures that can be checked by an image model. A moving rover can collect



this information at different locations. However, the results from the reviewed papers cannot be assumed to apply directly to AgriRover Pro, because its final hardware, software, and test conditions are not yet known.

AgriRover Pro is therefore proposed as a student-level design that starts with basic movement, obstacle detection, soil readings, camera capture, and a simple dashboard. The first version should be small, safe, and easy to test. Image recognition, battery life, navigation, network loss, and total cost should be measured carefully. More advanced tasks such as automatic spraying, seed sowing, or disease prediction should be added only after separate testing. The project can become more useful through step-by-step development, clear reporting, and feedback from people who understand farming.

Limitations of this Review

This review is based on the three research papers supplied for the assignment and does not cover every publication on agricultural robots. The papers use different hardware, test setups, and measures, so their reported values are not directly comparable. AgriRover Pro is a proposed concept; no prototype test results are claimed in this paper.

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