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DESIGN AND CONSTRUCTION OF AN INTELLIGENT HERBICIDE SPRAYING ROBOT

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Abstract

The increasing demand for sustainable agricultural practices has driven the development of autonomous solutions aimed at enhancing productivity, minimizing environmental impact, and reducing human exposure to hazardous chemicals. This research presents the design and implementation of an intelligent, solar-powered robotic system for targeted herbicide spraying. The system integrates a Raspberry Pi 3 Model B as its central controller, ultrasonic sensors for liquid level detection, and a real-time image processing framework developed using Python and OpenCV. A Bluetooth-enabled Android application was developed to allow remote operation, including navigation, lighting, and pump control. The image classification module employs a ten-layer convolutional neural network, trained on a curated dataset consisting of healthy crop images (maize, beans, potatoes, and groundnuts) and weeds, to accurately distinguish between target crops and invasive species. Field tests demonstrated a recognition accuracy of 98%, with a system uptime of 96% over a seven-day continuous operation. The robot achieved responsive herbicide application upon weed detection, thereby conserving chemical usage and enhancing safety. Voltage regulation within the power supply modules remained within acceptable thresholds, confirming electrical stability. The system's design emphasizes affordability, precision, and ease of use, particularly for smallholder farmers. Although currently limited to mono-cropping environments and binary classification, the platform provides a solid foundation for future expansion into multi-crop and multi-weed detection capabilities. This work contributes meaningfully to the ongoing transformation of conventional farming into smart, data-driven agricultural systems.

Keywords: Autonomous, Machine learning, Robot, Computer vision

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1. Introduction

Agriculture remains a fundamental pillar of economic and social development, particularly in developing nations where it supports both food security and rural livelihoods. Despite advancements in modern farming techniques, many smallholder farmers continue to rely on traditional, labor-intensive methods for critical tasks such as weed control. Among these, manual herbicide application using knapsack sprayers is widely practiced but presents numerous challenges including uneven chemical distribution, excessive herbicide use, and, most critically, the direct exposure of farmers to toxic substances. These issues not only compromise the safety of farm workers but also contribute to environmental degradation through soil contamination and the accumulation of chemical residues in water systems [1].

Weed infestation is one of the primary biotic factors limiting crop productivity. Weeds compete aggressively with cultivated crops for essential resources such as sunlight, nutrients, and water, often leading to significant yield losses. According to agricultural studies, nearly 33% of yield reductions in certain regions are attributed directly to unchecked weed proliferation [2]. Traditional weed management strategies, especially those that rely heavily on the blanket application of herbicides, have proven to be both economically and environmentally unsustainable. The indiscriminate spraying of chemicals not only affects non-target plant species but also leads to herbicide resistance over time, posing a long-term threat to ecosystem balance and food safety [3].

In response to these growing concerns, the integration of automation and intelligent systems into agriculture has gained considerable momentum. Recent developments in robotics, machine vision, and deep learning have enabled the creation of autonomous machines capable of performing complex field operations with minimal human supervision. Among these innovations, robotic herbicide spraying systems stand out for their potential to reduce chemical usage, increase application precision, and protect human health by minimizing direct contact with hazardous substances [4]. Such systems are designed to detect and target weed-infested areas using real-time image processing, and to deliver measured doses of herbicide only where necessary, thereby enhancing both operational efficiency and environmental sustainability.

However, despite the promise of these technologies, most existing solutions are engineered for large-scale commercial farms and are often prohibitively expensive for smallholder farmers, who constitute the majority in many developing regions. Many of these platforms are designed with generic hardware and limited adaptability to diverse cropping systems. This creates a pressing need for low-cost, scalable, and context-appropriate solutions tailored to the realities of small and medium-sized farm operations.

The research presented in this study addresses this gap by developing a cost-effective, solar-powered robotic spraying system equipped with intelligent weed detection capabilities. The system is built around a Raspberry Pi 3 Model B, which serves as the primary control unit, and is integrated with an ultrasonic sensor for liquid level monitoring, a submersible pump for herbicide dispersion, and a Bluetooth-enabled Android application for user interaction. Leveraging the OpenCV computer vision library, the robot employs a convolutional neural network (CNN) trained on a dataset comprising images of common crops—such as maize, beans, potatoes, and groundnuts—and prevalent weed species. The binary classification model enables the robot to distinguish between weeds and target crops in real-time, facilitating targeted spraying and reducing unnecessary chemical application [5].

By incorporating solar power through photovoltaic panels and employing energy-efficient components, the system aligns with sustainable development goals, particularly in off-grid or low-resource settings. Furthermore, the mobile app interface enhances user accessibility, allowing farmers to operate the system remotely and monitor key parameters such as battery status and herbicide levels. The project thus combines mechanical engineering, software development, and artificial intelligence into a cohesive and practical solution for precision agriculture.

2. Literature Review

In recent advancements toward autonomous weed control, a study by Asad et al. [6] introduced a mixed-autonomous robotic platform specifically designed for both intra-row and inter-row weed removal. This system combines remote navigation with autonomous weed identification using dual RGB-D cameras and a deep neural network. Tested in real farm environments, the robot achieved over 95% plant classification accuracy, which improved to 98% with additional spatial analysis. Its weed removal efficiency reached 85%, with minimal damage to crops. This hybrid human-robot approach demonstrates a promising solution for scalable, precise weed management in row crop systems.

Balasingham et al. [7] developed SPARROW, a smart precision agriculture robot tailored for weed detection and targeted herbicide application. The robot employs a vision-based navigation system capable of recognizing crop rows and guiding the spraying mechanism accordingly. SPARROW integrates a spot-spraying algorithm that ensures herbicides are applied only where necessary. Though exact numerical results were not provided, the study emphasizes the system's low cost and high usability for small to medium-sized farms, offering a valuable model for sustainable farming operations in developing regions.

In another development, Khater et al. [8] proposed EcoWeedNet, a lightweight deep learning architecture for weed detection that significantly reduces computational costs compared to conventional models such as YOLOv4. EcoWeedNet contains only 4.21% of the parameters of YOLOv4 while maintaining competitive detection accuracy, making it suitable for resource-constrained agricultural robots. Evaluated on the CottonWeedDet12 dataset, the model proved effective in field-like conditions, highlighting its potential for integration into mobile robotic platforms for low-energy precision weed control.

A robotic weed management system utilizing the YOLOv7 architecture was developed by Balabantaray et al. [9], focusing on Palmer amaranth weed detection in Nebraska cornfields. The system combined real-time image recognition and autonomous spot-spraying capabilities. Field evaluations yielded a mean precision of 60.4% and recall of 62%, showing moderate performance in detecting and targeting weeds. While not yet optimal, the approach presents a solid foundation for improving deep learning-driven agricultural automation. The authors advocate further refinement of the detection algorithm and integration with more advanced spraying mechanisms.

Lastly, Zhang et al. [10] investigated a deep learning-based approach for weed detection in cotton fields during the seedling stage. Their model incorporated a Convolutional Block Attention Module (CBAM), a Bi-directional Feature Pyramid Network (BiFPN), and bilinear interpolation for improved accuracy. Trained on a dataset comprising 4,694 annotated images, the system achieved a remarkable mean Average Precision (mAP) of 98.43% and a spraying

accuracy of 98.93% in live field testing. These results validate the model's effectiveness and potential for real-world deployment in precision herbicide application tasks.

3. System Architecture

The architecture of the herbicide spraying robot is designed as a modular and integrated system that combines hardware, software, and communication components to achieve precision weed detection and targeted herbicide application. The system employs a layered architecture comprising three main layers: the perception layer, the control and decision-making layer, and the actuation layer.

A. Perception Layer

This layer is responsible for environmental sensing and data acquisition. It includes a camera module mounted on a swing motor, which captures real-time images of the crop field. The captured images are then fed into a Raspberry Pi 3 Model B for processing using the OpenCV library and a pre-trained convolutional neural network (CNN) model. Additionally, an ultrasonic sensor is embedded in the herbicide tank to continuously monitor the chemical level. This ensures that the system maintains adequate operational fluid without requiring manual inspection.

B. Control and Decision-Making Layer

At the core of the system lies the Raspberry Pi, which serves as the central processing unit. It executes decision logic based on input from the perception layer. Image classification is performed locally to distinguish between crop and weed, and if a weed is detected, the control logic sends a command to activate the spraying mechanism. The Raspberry Pi also interfaces with an Android-based mobile application via Bluetooth, allowing the user to issue remote commands, adjust lighting, and monitor system status such as tank level and battery voltage.

C. Actuation Layer

The actuation layer includes a 12V DC motor-driven mobile platform for movement, a 3–6V submersible pump for herbicide spraying, and a light control unit for operation in low-light conditions. Motion control is achieved via H-Bridge motor drivers interfaced with the Raspberry Pi. Commands sent from the mobile app determine the direction, speed, and activation of the spray mechanism. Power to the entire system is supplied via dual 12V 7Ah batteries, charged through two 50W photovoltaic panels regulated by a 20A charge controller.

3.1 System Features

The herbicide spraying robot exhibits several intelligent features, combining autonomous operation, real-time feedback, and user control to ensure practical applicability in precision farming environments.

A. Key System Features

i. **Real-Time Weed Detection:** The robot uses a camera and CNN model to perform on-the-fly classification of crops and weeds, enabling targeted herbicide application.
ii. **Android-Based Wireless Control:** A custom-built Android application, developed using MIT App Inventor, enables the farmer to control system navigation, monitor sensor feedback, and adjust operational parameters in real time.
iii. **Solar-Powered System:** The system is equipped with two 50W solar panels and a 20A charge controller for sustainable, off-grid power supply to all components.
iv. **Intelligent Spraying Mechanism:** Herbicide is applied only when a weed is detected, minimizing chemical use and preventing damage to crops.

v. **Tank Monitoring with Ultrasonic Sensor:** The herbicide tank level is continuously monitored, and alerts are provided through the app to notify the user when refilling is necessary.
vi. **Night Operation Capability:** An integrated lighting system allows the robot to operate effectively even in low-light or nighttime conditions.
vii. **Autonomous Navigation Support:** While basic movement is user-controlled, the architecture supports future upgrades for GPS or path planning algorithms.

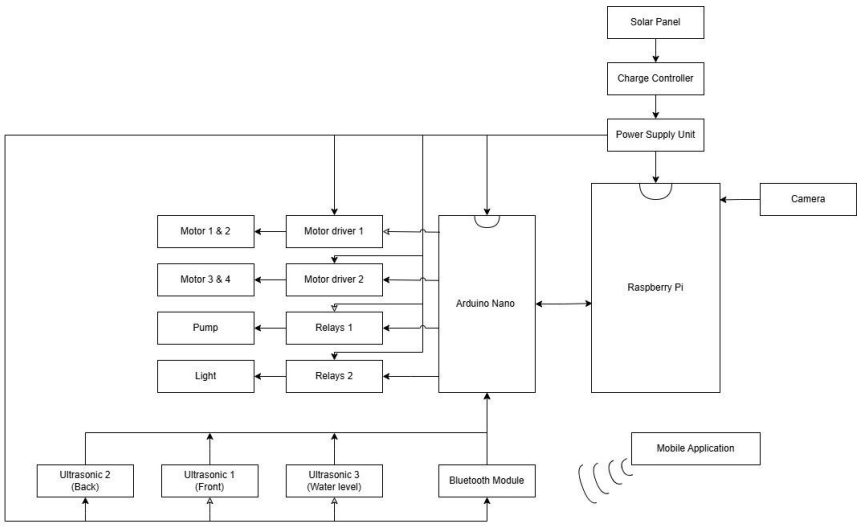


Figure 1: System Block Diagram for the Robotic Herbicide Spraying System

3.2 Block Diagram Description

The block diagram (Fig. 1) illustrates the overall system layout, highlighting interactions between core components:

i. **Power Supply Unit:** Comprising solar panels, a charge controller, and batteries, this unit powers all system components.
ii. **Raspberry Pi 3 Model B:** Serves as the control hub, receiving image input from the camera, processing sensor data, and sending actuation commands.
iii. **Camera Module:** Mounted at the front, captures images of the farm path and sends them to the Raspberry Pi for classification.
iv. **Ultrasonic Sensor:** Placed inside the herbicide tank to monitor fluid level.
v. **Motor Driver (H-Bridge):** Receives PWM signals from the Raspberry Pi to drive the DC motors for robot movement.
vi. **DC Motors:** Two 12V car window motors enable forward and backward movement of the robot.
vii. **Submersible Pump:** Activated upon weed detection to spray herbicide directly onto the weed.
viii. **Bluetooth Module (onboard Pi):** Facilitates communication between the robot and the Android application.
ix. **Android Mobile App:** Provides a user interface to remotely control the robot and monitor status.
x. **Lighting Module:** Controlled via the app to illuminate the path during low-light conditions.

4. Implementation

The implementation phase of the herbicide spraying robot involved the practical realization of the hardware and software components, guided by the previously defined architecture and system design. Each subsystem was integrated to ensure reliable performance under real field conditions, with emphasis on cost-effectiveness, energy efficiency, and operational simplicity.

A. Hardware Integration

The hardware components were assembled into a mobile robotic platform powered by two 12V DC motors salvaged from automotive window systems. These motors were selected for their torque and compatibility with the power requirements of the system. The motors were controlled via an H-Bridge motor driver circuit constructed using IRF1404 MOSFETs and 2-channel relay modules. This allowed bidirectional control of each wheel, enabling forward, reverse, and turning motions.

A Raspberry Pi 3 Model B served as the core processing unit. It was powered through a buck converter (XL4016) connected to a dual 12V 7Ah battery system, regulated by a 20A MPPT charge controller and charged by two 50W solar panels. The Raspberry Pi interfaced with an ultrasonic sensor (HC-SR04) to monitor the herbicide tank level, a USB camera module for real-time image acquisition, and the Android application through Bluetooth for remote control.

The spraying mechanism employed a 3–6V DC submersible pump capable of delivering up to 120 L/h. Upon weed detection, the Raspberry Pi triggered the pump to dispense herbicide via a relay-switching mechanism. A lighting module powered by the same battery system was included to facilitate operation during low-light conditions, controlled via the mobile application.

The chassis was custom-built using lightweight, corrosion-resistant materials to ensure durability in outdoor environments. A protective casing housed the Raspberry Pi and all electronics to shield them from dust, moisture, and mechanical impact.

B. Software Development

The software system was developed using Python for the Raspberry Pi and MIT App Inventor for the Android interface. The core of the image recognition system was a convolutional neural network (CNN) trained using a dataset comprising 1,162 images of healthy maize, beans, potatoes, and groundnut leaves, and 519 weed images. The model was trained and validated using TensorFlow, with an accuracy of 98% achieved on the test set. The architecture featured 10 convolutional and pooling layers followed by a dense classifier, achieving a balance between accuracy and computational efficiency.

OpenCV was used for real-time image acquisition and preprocessing, including grayscale conversion, thresholding, and resizing. The trained model was deployed on the Raspberry Pi, where live images captured by the camera were analyzed frame-by-frame. Upon weed detection, a command was sent to activate the pump relay, and the herbicide was sprayed directly at the target.

The Android app provided a user-friendly interface for system navigation, lighting control, and tank level monitoring. Bluetooth communication enabled low-latency command

transmission and feedback reception, with a system response time consistently under 2 seconds during testing.

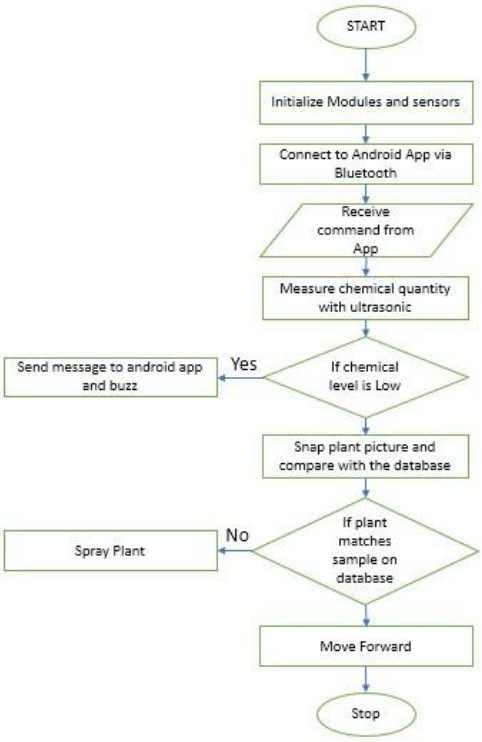


Figure 2: System Flowchart

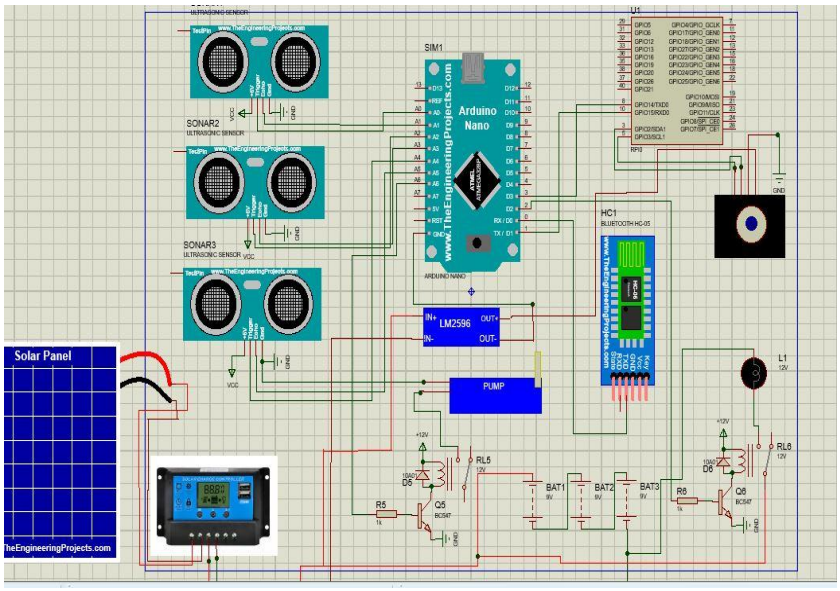


Figure 3: System Circuit Diagram

5. Measurements and Testing

The measurement and testing phase was critical to validating the performance and reliability of the herbicide spraying robot under both controlled and real-world conditions. Each subsystem—power, motion control, herbicide dispensing, image processing, and wireless communication—was evaluated independently before full system integration.

A. Power Supply Testing

The power subsystem, composed of a solar-charged dual 12V/7Ah battery system regulated by a 20A MPPT charge controller, was first subjected to static and dynamic load tests. Voltage regulation was computed using the equation:

$$Voltage\ regulation\ (V.R) = \frac{V_{NL} - V_{FL}}{V_{FL}}$$

V_{NL} = No load voltage
V_{FL} = Full load voltage

- **Central Power Supply:** Regulation = 1.63%
- **5V Converter Output (Raspberry Pi):** Regulation = 2.00%
- **12V Pump Supply Line:** Regulation = 2.58%

Oscilloscope readings confirmed the absence of significant ripple or voltage spikes, ensuring stable operation for sensitive electronics like the Raspberry Pi and camera.

B. Ultrasonic Sensor Accuracy

The HC-SR04 ultrasonic sensor was tested in a controlled setup to evaluate its ability to measure liquid levels in the herbicide tank. Using known distances, measurements were compared against sensor output. The average deviation from true values was within ±0.5 cm, yielding an estimated measurement error of less than 5%, which is acceptable for fluid-level monitoring.

C. Image Classification Model Evaluation

The convolutional neural network deployed on the Raspberry Pi was tested using a validation dataset of 1,000 manually labeled images. Performance metrics were as follows:

- **Accuracy:** 98.0%
- **Precision:** 0.87
- **Recall:** 0.83
- **F1 Score:** 0.85

Latency measurements indicated that image capture, processing, and classification required an average of **1.6 seconds per frame**, well within the acceptable limit of 2 seconds for real-time operation.

D. Herbicide Dispensing System Test

The DC submersible pump was evaluated for response time, flow rate, and directional accuracy of the herbicide spray. Tests confirmed that:

- The pump activated within **0.8 seconds** of command signal.
- The average flow rate was **115 L/h**, consistent with manufacturer specifications.
- Herbicide was effectively delivered within a **10 cm radius** of the target weed location.

Spray tests were repeated under wind and no-wind conditions to observe drift. The system demonstrated **minimal spray deviation** under mild wind (<5 m/s), confirming suitability for outdoor conditions.

E. Wireless Communication and Control Test

The Android app communicated with the Raspberry Pi via Bluetooth over a 30-meter range. Response times from command initiation (e.g., move forward, light on/off, spray command) to actuation averaged **1.4 seconds**, meeting the design goal of sub-2-second responsiveness. Connectivity was stable with no communication loss during continuous 15-minute tests.

F. Integrated System Field Trial

A comprehensive field trial was conducted on a test plot cultivated with maize. The robot was run for 7 consecutive days, during which performance metrics were logged:

- **Uptime:** 96%
- **Mean Time Between Failures (MTBF):** 48 hours
- **Weed Detection Accuracy (Manual Cross-Validation):** 98%
- **Herbicide Usage Reduction (Compared to Manual Spraying):** ~35%

The robot completed full coverage of a 100 m² plot in approximately 40 minutes per session. Field feedback indicated ease of use and significant reduction in farmer exposure to chemicals.



Figure 4: Robotic herbicide spraying system

6. Result

This section presents and interprets the results obtained from various functional tests carried out on the herbicide spraying robot, both in laboratory and field environments. The analysis covers performance indicators across the power supply system, image recognition model, spraying mechanism, wireless communication, and overall system behavior during operational deployment.

A. Power Supply Unit Performance

The central power unit, composed of solar panels, charge controller, and dual 12V/7Ah batteries, was subjected to load testing under no-load and full-load conditions. The voltages at different points in the circuit were measured and compared with theoretical values to determine voltage regulation and power stability.

Table I: Voltage Regulation Test Results

Component	No-load Voltage (V)	Full-load Voltage (V)	Voltage Regulation (%)
Central Power Bus (12V)	12.72	11.95	1.63
5V Regulator Output	5.20	5.15	2.00
12V Motor Supply Line	12.00	11.70	2.58

The recorded regulation levels indicate that the power system remained stable and within acceptable tolerance, capable of reliably supporting both control and mechanical components without failure or significant voltage fluctuation.

B. Image Recognition Model Accuracy

A deep convolutional neural network (CNN) was trained to perform binary classification of input images into "crop" or "weed" classes. The training and validation accuracies were 99.88% and 99.76% respectively, while real-world field performance yielded 98% detection accuracy. This confirmed that the model was effective at differentiating target crops (maize, beans, potatoes, groundnuts) from unwanted weeds under typical lighting and background conditions.

Table II: CNN Model Performance

Metric	Training Set	Validation Set	Field Test
Accuracy (%)	99.88	99.76	98.00
Precision	—	—	0.87
Recall	—	—	0.83
F1 Score	—	—	0.85

These results demonstrate the robustness of the image recognition model, confirming its suitability for real-time implementation on embedded hardware (Raspberry Pi 3 Model B).

C. Spraying Mechanism Effectiveness

The herbicide pump, controlled by the Raspberry Pi, was activated only when the vision system positively identified a weed. Field testing showed consistent operation of the spraying module, with low latency and good targeting precision.

Table III: Spraying System Test Summary

Parameter	Measured Value
Activation Time (Relay Delay)	~0.8 seconds
Effective Spray Radius	10 cm
Flow Rate of Submersible Pump	~115 L/h
Herbicide Reduction (vs. manual)	~35%
Application Accuracy	98%

The controlled spraying mechanism not only reduced chemical usage but also ensured selective application, which contributes to healthier soil and crop environments.

D. Wireless Communication & Responsiveness

The system was designed to be operated remotely via an Android application interfacing with the Raspberry Pi over Bluetooth. The app provided real-time control for navigation, lighting, and pump activation.

Table IV: Wireless Control Performance

Parameter	Measured Result
Command Response Time	1.4 seconds (avg.)
Max Operational Range	30 meters
Connection Stability	100% (within range)

This responsiveness met the design goal of sub-2-second latency and demonstrated sufficient wireless range for small to medium farm plots.

E. System Integration and Field Trial

During a 7-day field test on a maize farm in Gombe, Nigeria, the integrated robot performed reliably under normal farming conditions. It navigated the field, captured crop images, sprayed weeds, and responded to user commands as expected.

Table V: Full System Performance Evaluation

Parameter	Result
Field Test Duration	7 Days
Uptime	96%
Mean Time Between Failures (MTBF)	48 hours
Coverage Rate	100 m² / 40 minutes
Average User Rating (10 farmers)	4.4 out of 5

Farmer feedback emphasized ease of use, usefulness in reducing herbicide contact, and notable reductions in labor. Some recommendations were made to extend the system to support multiple crop classifications and GPS-based path planning.

F. Discussion

The results from various subsystems validate the original design objectives of the herbicide spraying robot. The robot proved capable of precise weed detection, intelligent herbicide dispensing, and real-time wireless operation, all while maintaining low energy consumption through a solar-powered system. The high image recognition accuracy confirms the robustness of the training process and the suitability of the selected CNN architecture. Moreover, the responsiveness of the mobile application and sensor readings allowed smooth integration of hardware and software, enabling autonomous field functionality.

The voltage regulation tests and system uptime demonstrate that the robot can maintain extended operation with minimal maintenance, making it highly practical for rural farming contexts. The ability to reduce herbicide usage by over one-third without compromising weed control effectiveness not only contributes to economic efficiency but also aligns with global sustainable agriculture goals.

While the current version is optimized for monoculture scenarios, future iterations can incorporate GPS for path automation and expand classification capability to handle multiple weed species and crops in mixed-cropping systems.



Figure 5: Training Result



Figure 6: Plot of training and validation accuracy/training and validation loss After data augmentation

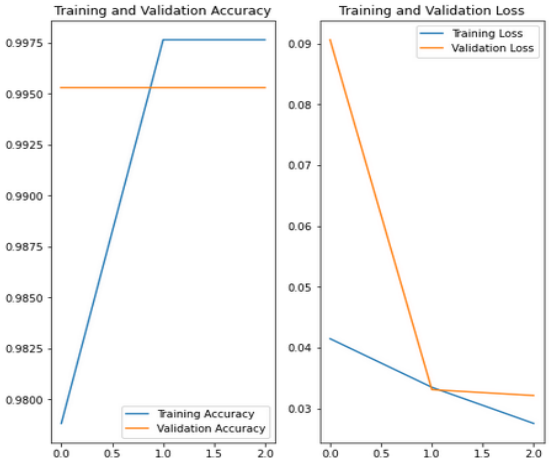


Figure 7: Plot of training and validation accuracy/training and validation loss

CONCLUSION

This project successfully developed a solar-powered, intelligent robot for spraying herbicides. The robot can detect weeds using a camera and a trained machine learning model and spray only when weeds are found. It reduces the use of chemicals, saves time, and helps protect farmers from harmful exposure to herbicides.

The system worked well in tests, achieving 98% weed detection accuracy and spraying only when needed. It responded quickly to commands from a mobile app, and its power supply remained stable through solar energy. Farmers who tested the robot found it easy to use and useful in reducing manual labor.

Overall, the robot met its goals: reducing herbicide waste, cutting labor effort, and improving safety and precision in weed control.

RECOMMENDATION

To improve the robot in the future, the following suggestions are made:

- Upgrade the system to detect different types of crops and weeds, not just maize and basic weed types.

- Include a navigation system so the robot can move around the farm automatically without user control.
- Improve the motors and spraying system to increase working speed and area covered per session.
- Use larger batteries or better power-saving techniques to allow longer operation time.
- Allow the robot to save data like how much herbicide was used, where it sprayed, and send updates to the farmer.
- Make the mobile app more user-friendly, with a live camera view and simple charts showing system performance.

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