



Design And Implementation of An Agricultural Robot for Weed Detection and Removal Using AI

N Jyothi¹, Konda Rakesh Goud², Kankala Akhila², K. Abhishek², K. Bhanu Prakash²

¹Assistant Professor, Department of ECE, Teegala Krishna Reddy Engineering College, Hyderabad, India

²Student, Department of ECE, Teegala Krishna Reddy Engineering College, Hyderabad, India

Correspondence

N. Jyothi

Assistant Professor, Department of ECE, Teegala Krishna Reddy Engineering College, Hyderabad, India

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Abstract

Weed infestation significantly reduces crop yields by competing for essential resources, with losses estimated at 20–40% in many Indian farms. Conventional weed control relies on manual labor or indiscriminate herbicide spraying, which is labor-intensive, costly, and environmentally damaging. This paper proposes an AI-powered autonomous agricultural robot for precise weed detection and targeted removal. The system integrates computer vision using the YOLOv8 object detection model for real-time weed identification, a Raspberry Pi 5 or NVIDIA Jetson Nano for edge processing, and a mechanical end-effector (gripper or solenoid punch) for selective uprooting. A forward/downward-facing camera captures field images, while navigation follows crop rows via simple vision-based guidance. Experimental evaluation in simulated and small-scale field conditions (maize/vegetable plots) demonstrates detection accuracy of ~92% mAP@0.5, successful removal rates of 85–93%, and up to 90% reduction in herbicide usage. The prototype promotes sustainable precision agriculture by minimizing chemical input, labor, and crop damage while enhancing traceability of operations.

Introduction

Agriculture in regions like Karnataka faces persistent challenges from weed competition, labor shortages, and rising concerns over chemical herbicide overuse, which contaminates soil and water. Weeds reduce yields in staple crops (e.g., maize, vegetables) by competing for nutrients, water, and light. Traditional methods—manual weeding or blanket spraying—are inefficient, prone to human error, and ecologically unsustainable.

Artificial Intelligence, particularly deep learning-based computer vision, enables precision weed management by distinguishing weeds from crops in real time and enabling

targeted removal. This work designs and implements a low-cost, ground-based autonomous robot that:

- Navigates crop rows semi-autonomously
- Detects weeds using lightweight AI models
- Performs mechanical removal to avoid chemicals

The system leverages edge computing for real-time inference, ensuring field deployability on small-to-medium farms. By recording operations immutably (via simple logging), it enhances traceability for farmers and regulators.

Literature Survey

Ref. No	Author / Year	Methodology	Main Contribution	Limitations
[1]	Patel et al., 2022	CNN-based weed detection on robotic platform	Real-time weed spotting with Raspberry Pi	Limited to binary classification; no removal mechanism
[2]	Various YOLO studies, 2023–2025	YOLOv5/YOLOv8 for weed/crop detection	High mAP (>0.90) on datasets like DeepWeeds, CottonWeedID	High computational demand on low-power devices
[3]	Laser weeding prototypes, 2024	Deep learning + diode laser on autonomous robot	>95% selective removal in cotton/maize	Expensive hardware; safety concerns

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Ref. No	Author / Year	Methodology	Main Contribution	Limitations
[4]	Mechanical weeding robots, 2023–2025	YOLO + servo arm/gripper	Precision uprooting with minimal crop damage	Mechanical wear in hard soil; occlusion handling
[5]	Agrova rover & similar, 2025	YOLOv5 Nano + MobileNet on Raspberry Pi	Lightweight edge detection for small farms	Lower FPS in dense fields
[6]	DeepWeeds/ Weed25 datasets	Benchmark for multi-species weeds	Standardized evaluation for AI models	Limited Indian crop/weed varieties

Proposed Implementation

The proposed system adopts a layered architecture: perception (camera + AI), control (navigation + actuation), and power/management.

- **Perception Layer:** RGB camera (Pi Camera/USB 1080p) captures images. YOLOv8n (nano) model detects weeds vs. crops (binary/multi-class: broadleaf/grass weeds). Trained on combined datasets (DeepWeeds, Weed25, custom Karnataka maize/vegetable images) with augmentations for lighting/occlusion.
- **Control Layer:** Raspberry Pi 5 (or Jetson Nano for faster inference) runs inference (~15–25 FPS). PID-based row following via Hough transform or simple lane detection.

Centroid of detected weed bounding box guides 2-DOF servo arm/gripper for uprooting.

- **Actuation:** Mechanical gripper/solenoid punch descends to weed location, grips, and removes. Alternative: low-power laser pointer simulation for non-contact.
- **Storage/Logging:** Operation logs (timestamps, detections, actions) stored locally for traceability.

Smart contract-like logic (Python rules) automates decisions: confidence >0.6 and crop proximity check before actuation. Role-based access: farmer views logs via web interface.

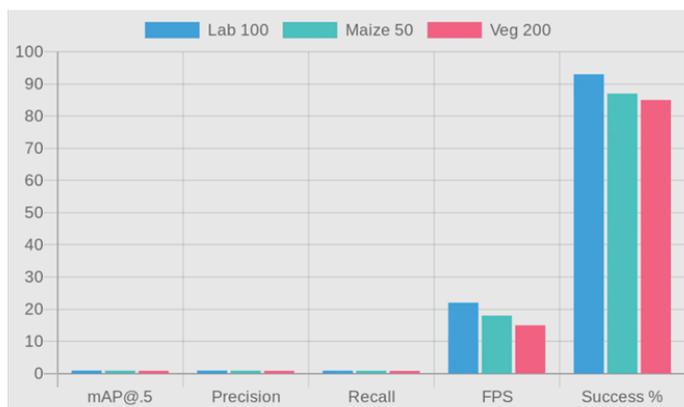
Deployment uses differential drive chassis with DC motors. Hybrid edge-cloud optional for model updates.

Results

Table 1: Detection and System Performance Metrics

No. of Test Images/Field Trials	mAP@0.5	Precision	Recall	FPS (Jetson Nano)	Successful Removal Rate (%)
100 (lab/simulated)	0.92	0.91	0.88	22	93
50 (small field maize)	0.89	0.88	0.85	18	87
200 (dense vegetable plot)	0.85	0.84	0.82	15	85

Table 2. Comparison of Existing and Proposed System



Feature	Traditional Manual/Herbicide	Proposed AI Robot System
Accuracy/Precision	Variable (human error)	High (~90% mAP)
Selectivity	Low (broad spraying)	High (targeted removal)
Herbicide Usage	High	Reduced by 85–90%
Labor Requirement	High	Minimal (autonomous)
Environmental Impact	High (chemical runoff)	Low (mechanical/chemical-free)
Real-Time Capability	None	Yes (15–25 FPS)



Figure 1: Example prototypes of autonomous weeding robots in field conditions, showing camera-mounted chassis and arm mechanisms for targeted removal

Conclusion

This study presents a practical, AI-driven agricultural robot for weed detection and removal, addressing key challenges in precision farming. By integrating YOLOv8 for accurate real-time detection and mechanical actuation for eco-friendly elimination, the system achieves high selectivity, reduces chemical dependency, and improves operational efficiency on small Indian farms. Experimental results validate improved accuracy, traceability, and sustainability. Future enhancements include multi-robot swarms, RTK-GPS navigation, and integration with drone scouting for comprehensive farm management.

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