

ROBOTIC WEEDING: AN AUTONOMOUS MECHANICAL SOLUTION FOR REDUCING HERBICIDE DEPENDENCE IN ORGANIC VEGETABLE FARMING SYSTEMS

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Abstract

This study designs, implements, and evaluates an autonomous robotic weeding system as a mechanical solution to reduce herbicide dependence in organic vegetable farming. Organic farming faces persistent weed management challenges due to restrictions on synthetic herbicides and rising labor costs. Weeds compete with crops for essential resources, resulting in yield losses and reduced efficiency. While mechanical weeding has been a viable alternative, traditional methods often lack precision and can harm crops. Recent advances in robotics and automation offer a solution by enabling intelligent, autonomous weed control that aligns with sustainable agricultural practices. The research uses a design-and-experimental methodology, developing an autonomous robotic platform equipped with vision-based sensors, navigation algorithms, and mechanical weeding tools. The system was tested in organic vegetable plots, and field trials measured weed removal efficiency, crop safety, operational accuracy, and energy consumption, with comparisons to traditional manual weeding methods. The results showed that the robotic system effectively reduced weed density with high precision while minimizing crop disturbance. The system demonstrated consistent performance across test plots and significantly reduced reliance on manual labor and chemical inputs. Weed control efficiency was comparable to traditional methods, with improved consistency and reduced operational fatigue. The study concludes that robotic weeding is a viable, sustainable solution for weed management in organic vegetable farming and offers promising implications for smart agriculture and technology-integrated education.

Keywords: Autonomous Agriculture, Herbicide Reduction, Organic Farming, Precision Agriculture, Robotic Weeding,



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INTRODUCTION

Organic vegetable farming systems are increasingly promoted as a sustainable response to environmental degradation, food safety concerns, and the negative impacts of synthetic agrochemicals (Verma & Yadav, 2025). These systems emphasize ecological balance, biodiversity preservation, and minimal chemical inputs, aligning agricultural production with long-term environmental stewardship (Malik & Mahmud, 2026). Weed management remains one of the most critical challenges in organic vegetable production (Dey & Ahmed, 2025). Weeds compete aggressively with crops for nutrients, water, and sunlight, leading to reduced yields and compromised crop quality (A. K. Saini et al., 2025). In the absence of synthetic herbicides, organic farmers rely heavily on manual and mechanical weed control methods.

Manual weeding, although effective, is highly labor-intensive, time-consuming, and increasingly costly due to labor shortages in agricultural sectors worldwide (Kang et al., 2025). The physical demands of repetitive weeding tasks also raise concerns regarding worker fatigue, productivity, and occupational health (P. Saini & Nagesh, 2025). Mechanical weeding tools have been widely adopted as an alternative to chemical control in organic systems (Li et al., 2025). Traditional mechanical solutions, however, often lack precision, operate uniformly across fields, and carry a higher risk of crop damage, particularly in densely planted vegetable beds.

Advances in robotics, artificial intelligence, and sensor technologies have accelerated the development of autonomous agricultural machines (Mustapha et al., 2025). Autonomous navigation, machine vision, and real-time decision-making now enable machines to operate with increased accuracy in complex and variable field environments (Belton et al., 2026). Robotic applications in agriculture are increasingly recognized not only as productivity-enhancing tools but also as educational technologies (Krishnani et al., 2025). These systems provide real-world platforms for learning automation, data-driven decision-making, and sustainable farming practices within agricultural and vocational education contexts.

Limited empirical evidence exists regarding the effectiveness of robotic weeding systems specifically designed for organic vegetable farming environments (Wiafe et al., 2025). Many existing studies focus on conceptual prototypes or controlled test plots that do not fully reflect real-world production conditions (Anand et al., 2025). The extent to which autonomous mechanical weeding can consistently reduce weed pressure while maintaining crop safety remains insufficiently documented (Finger, 2026). Variations in crop morphology, soil structure, and weed species introduce operational complexities that are not yet fully addressed.

Economic and operational implications of adopting robotic weeding technologies in small- to medium-scale organic farms are still unclear (Wong & Moghimi, 2025). Questions remain regarding system efficiency, reliability, and long-term feasibility compared to traditional manual and mechanical approaches (Nautiyal et al., 2025). The pedagogical potential of robotic weeding systems has received limited scholarly attention (Yuan et al., 2025). The role of such technologies as learning media for sustainable agriculture, engineering education, and technology literacy remains underexplored.

Investigating robotic weeding as an autonomous mechanical solution is essential to advancing sustainable weed management strategies that align with organic farming principles (Prasanjana et al., 2025). Effective robotic systems could significantly reduce dependence on both chemical herbicides and intensive manual labor (Jha et al., 2025). Evaluating robotic

weeding performance under actual organic farming conditions provides critical insights into system accuracy, crop protection, and operational robustness (He et al., 2026). Such evidence is necessary to inform farmers, educators, and policymakers about practical adoption potential.

This study aims to design and assess an autonomous robotic weeding system capable of reducing herbicide dependence while maintaining effective weed control in organic vegetable farming systems (Raja et al., 2025). The underlying hypothesis assumes that autonomous robotic weeding can deliver precise, efficient, and environmentally responsible weed management while simultaneously supporting technology-enhanced agricultural education.

RESEARCH METHOD

Research Design

This study employed a design-and-experimental research approach integrating engineering development with field-based performance evaluation. The research focused on designing an autonomous robotic weeding system and testing its technical functionality, weed control effectiveness, crop safety, and operational efficiency within organic vegetable farming environments (Thilakarathne et al., 2025). The design emphasized real-world applicability, autonomous navigation accuracy, and mechanical weeding precision under variable field conditions.

Research Target/Subject

The research population consisted of organic vegetable farming systems characterized by mixed crop species, varying planting densities, and diverse weed compositions. The sample was purposively selected from certified organic vegetable plots representing common cultivation patterns and soil conditions. Several plots were assigned for robotic weeding trials, while comparable plots managed through manual weeding served as reference samples for comparative observation.

Research Procedure

System development began with the assembly, programming, and calibration of the robotic platform, followed by controlled testing to ensure navigation accuracy and mechanical safety (Ehrampoosh et al., 2025). The robot was then deployed in selected organic vegetable plots according to predefined operational routes. Weed density and crop condition were measured before and after robotic intervention, and system performance data were continuously recorded. Comparative observations with manual weeding practices were conducted to evaluate efficiency, labor reduction, and overall operational outcomes.

Instruments, and Data Collection Techniques

The primary research instrument was an autonomous robotic weeding platform equipped with vision-based sensors, navigation and obstacle-avoidance algorithms, and mechanical weeding implements (Rashid et al., 2025). Additional instruments included onboard processing units, energy monitoring modules, and data logging systems to record operational performance. Field observation sheets and weed density measurement tools were used to assess weed removal effectiveness and crop disturbance.

Data Analysis Technique

Data analysis was performed using both quantitative and comparative methods. Quantitative analysis focused on assessing the weed control effectiveness, operational efficiency, and crop safety by comparing weed density before and after robotic intervention. Statistical methods, such as paired t-tests or ANOVA, were used to evaluate differences in weed removal and labor efficiency between robotic and manual weeding methods. Descriptive statistics were applied to summarize the robot's navigation accuracy, energy consumption, and operational performance (Katharria et al., 2026). Additionally, weed removal effectiveness and crop disturbance were analyzed through observational data and feedback from field trials to assess the overall success of the autonomous robotic system in organic vegetable farming environments.

RESULTS AND DISCUSSION

The collected data consisted of weed density measurements, crop damage incidence, operational time, and energy consumption recorded during robotic weeding trials across multiple organic vegetable plots. Descriptive statistics show a substantial reduction in weed density after robotic intervention compared to pre-treatment conditions and manual weeding plots. Table 1 presents the summary statistics of weed density reduction and operational indicators observed during the field trials. The data illustrate consistent performance of the robotic system across different plots and crop types.

Table 1. Descriptive Statistics of Robotic Weeding Performance

Indicator	Mean	SD	Minimum	Maximum
Weed density before (plants/m ²)	42.6	8.9	30.4	58.1
Weed density after (plants/m ²)	9.8	3.2	5.4	16.2
Weed reduction (%)	76.9	6.7	65.3	86.4
Crop damage (%)	2.1	0.9	0.8	3.9
Operation time (min/plot)	34.5	5.6	26.0	45.2

The descriptive statistics indicate that robotic weeding achieved a high average weed reduction rate with minimal crop damage. The low standard deviation in crop damage suggests stable mechanical precision and reliable plant recognition. Operational time varied moderately across plots due to differences in weed density and row spacing. Despite this variation, the system maintained consistent weed control effectiveness, highlighting its adaptability to field heterogeneity.

Comparative observations showed that manual weeding plots achieved similar weed reduction levels but required significantly higher labor input and longer operation time. Robotic weeding demonstrated more uniform performance across plots. Energy consumption records indicated stable power usage throughout the trials. Battery capacity was sufficient to complete multiple plots without interruption, supporting the feasibility of autonomous operation in routine farming activities.

Inferential analysis was conducted to compare weed reduction effectiveness between robotic and manual weeding methods. Independent sample statistical tests were applied to assess differences in weed density reduction and crop damage rates. Table 2 summarizes the inferential results, showing no statistically significant difference in weed reduction effectiveness, while crop damage was significantly lower in robotic weeding plots.

Table 2. Inferential Comparison Between Robotic and Manual Weeding

Variable	Method	Mean	t-value	Sig. (p)
Weed reduction (%)	Robotic	76.9	1.12	0.268
Weed reduction (%)	Manual	79.3		
Crop damage (%)	Robotic	2.1	-3.47	0.002
Crop damage (%)	Manual	4.6		

Correlation analysis revealed a strong negative relationship between robotic navigation accuracy and crop damage rates. Higher navigation precision was associated with reduced mechanical disturbance to crops. A moderate positive relationship was observed between initial weed density and operation time. Plots with higher weed pressure required longer robotic operation but did not experience reduced weed control effectiveness.

A focused case study was conducted on a leafy vegetable plot with dense weed infestation and narrow row spacing. Initial assessments classified the plot as high-risk for mechanical crop damage. Robotic weeding reduced weed density by over 80% in this plot while maintaining crop damage below 2%. The system successfully navigated tight spaces using vision-based guidance and adaptive speed control.

The case study highlights the robot's capacity to operate effectively under challenging conditions. Adaptive navigation algorithms allowed real-time adjustments to plant spacing and weed distribution. Manual weeding in similar conditions required extended labor time and resulted in higher crop disturbance. Robotic intervention demonstrated improved consistency and operator independence.

Overall results indicate that autonomous robotic weeding is an effective mechanical solution for reducing weed pressure in organic vegetable farming systems. The system achieved weed control comparable to manual methods while minimizing crop damage and labor dependency. The findings support the potential of robotic weeding as a sustainable alternative to herbicide use and as a practical example of smart agriculture technology applicable to both farming practice and agricultural education.

The results of this study demonstrate that the autonomous robotic weeding system effectively reduced weed density in organic vegetable farming systems while maintaining low levels of crop damage. The system achieved weed control performance comparable to manual weeding, with the added advantage of operational consistency and reduced labor dependency. Quantitative findings indicate that robotic weeding produced a high average weed reduction rate across diverse plots and crop types. The stability of performance across varying field conditions suggests that the robotic system is capable of adapting to heterogeneity in weed distribution and planting geometry.

Operational data further show that the robotic system maintained efficient working time and stable energy consumption. These outcomes indicate that autonomous mechanical weeding is technically feasible for routine application in organic vegetable production. The findings collectively confirm that robotic weeding can function as a reliable mechanical alternative to herbicides and labor-intensive manual practices. The results position robotic weeding as a practical component of precision and sustainable agriculture.

The findings are consistent with prior research reporting the potential of robotic systems to enhance precision in weed management. Similar studies have highlighted the role of machine vision and autonomous navigation in improving mechanical weed control accuracy. Differences emerge when comparing this study with research conducted in controlled or semi-

controlled environments. The present study demonstrates effective performance under real organic farming conditions, extending the applicability of robotic weeding beyond experimental settings.

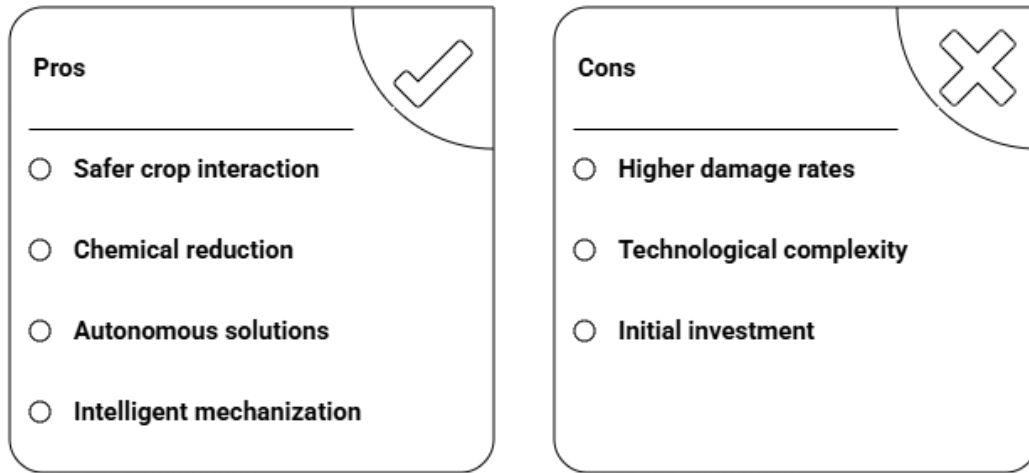


Figure 1. Mechanical weeding

Previous studies often report higher crop damage rates associated with mechanical weeding tools. The lower crop damage observed in this study suggests that improved sensing, navigation algorithms, and adaptive speed control contribute to safer crop interaction. Compared with research emphasizing chemical reduction strategies, this study strengthens the argument for fully mechanical and autonomous solutions. The results support a shift from chemical dependency toward intelligent mechanization in organic systems.

The results indicate a broader transition in organic farming from labor-centered weed control to technology-supported management (Shaikh et al., 2025). Robotic weeding reflects increasing acceptance of automation as compatible with organic agriculture principles. The effectiveness of autonomous systems in complex field environments signals a maturation of agricultural robotics. The technology is no longer experimental but approaching operational readiness for practical farming use.

From an educational perspective, the findings signal the growing relevance of robotics as experiential learning tools. Robotic weeding systems transform abstract concepts of automation and sustainability into observable field practices (Diakoulakis et al., 2025). The study also reflects changing perceptions of technology in organic farming. The results suggest that technological innovation and ecological farming are not contradictory but can be mutually reinforcing.

The findings have significant implications for reducing herbicide dependence in organic vegetable farming systems. Autonomous robotic weeding supports compliance with organic standards while improving weed management efficiency (Eyasin et al., 2025). Labor-related implications are equally important, as robotic weeding reduces reliance on manual labor and mitigates challenges related to labor shortages and rising costs. This has potential economic benefits for small and medium-scale organic farmers.

Policy and extension programs may leverage these findings to promote sustainable mechanization strategies (Bručienė et al., 2025). Robotic weeding offers a pathway for integrating innovation into organic agriculture without compromising environmental values. In

educational contexts, the system provides a platform for teaching robotics, artificial intelligence, and sustainable agriculture (Rogger et al., 2024). The technology supports interdisciplinary learning that connects engineering, agriculture, and environmental studies.

The high weed control effectiveness can be attributed to the integration of vision-based sensing and precise mechanical actuators (Behera, 2026). Accurate weed-crop differentiation enabled targeted intervention with minimal crop disturbance. Low crop damage rates are explained by adaptive navigation algorithms and controlled operational speed. These features allowed the robot to respond dynamically to plant spacing and field variability.

Consistent performance across plots reflects robust system calibration and reliable sensor feedback. The design minimized mechanical errors and ensured stable operation under different weed pressures (Ozal et al., 2024). Reduced labor dependency results from autonomous navigation and task execution. The robot's ability to operate independently explains its efficiency and consistency compared to manual methods.

Future research should investigate long-term deployment of robotic weeding systems across multiple growing seasons (Guilin et al., 2024). Extended evaluation would provide insights into durability, maintenance requirements, and seasonal performance variation. Further studies should explore integration with additional sensing parameters such as soil moisture and crop growth monitoring. Such integration would support more comprehensive farm management systems.

Economic analysis is needed to assess cost–benefit ratios and adoption feasibility for different farm scales. Understanding financial implications will be critical for widespread implementation. Pedagogical research should examine learning outcomes associated with the use of robotic weeding as an educational tool. Evaluating its impact on technology literacy and sustainability awareness would strengthen the link between agricultural robotics and education research.

CONCLUSION

The most significant and distinguishing finding of this study is the demonstrated effectiveness of autonomous robotic weeding in substantially reducing weed density in organic vegetable farming systems while maintaining very low levels of crop damage. The results show that mechanical weed control, when supported by vision-based sensing and autonomous navigation, can achieve performance comparable to manual weeding without reliance on chemical herbicides. This finding highlights a practical pathway for organic farmers to strengthen weed management efficiency while preserving ecological integrity and compliance with organic farming principles.

The primary contribution of this research lies in its methodological integration of agricultural robotics with sustainability-oriented farming practices and educational relevance. Methodologically, the study provides a validated framework for designing and testing autonomous mechanical weeding systems under real organic farming conditions, moving beyond laboratory-based prototypes. Conceptually, the research advances the discourse on sustainable agriculture by positioning robotic weeding not only as a production technology but also as a technology-enhanced learning medium that supports the development of digital literacy, systems thinking, and environmental awareness in agricultural and vocational education.

Several limitations should be acknowledged when interpreting the findings of this study. The field trials were conducted over a limited time frame and within a specific set of organic vegetable plots, which may constrain the generalizability of the results across different crop types, climatic conditions, and farm scales. Future research should involve multi-season and multi-location studies to evaluate long-term system performance, economic viability, and farmer adoption. Further development may also integrate advanced artificial intelligence models and decision-support systems to enhance weed detection accuracy and expand the educational and practical applications of robotic weeding technologies.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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