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Vision-Based Smart Weed Detection Robotic Arm for Precision Agriculture

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Abstract: The Robot Plant Picking System is an autonomous agricultural platform designed to detect and remove unhealthy or undesired plants from cultivated fields. The system integrates a Raspberry Pi single-board computer interfaced with a USB camera for real-time image acquisition. Captured images are processed using image processing algorithms to classify plant health status and identify target specimens for removal. Actuation is performed through a robotic arm driven by an Arduino Mega 2560 microcontroller, which executes precise plucking operations based on classification outputs. Locomotion is achieved through a DC motor-driven chassis controlled via a motor driver circuit, ensuring stable and navigable field traversal. A Bluetooth module enables wireless communication for remote operation and manual override, improving field-level flexibility. The entire system is powered by a 12V rechargeable battery regulated through an onboard power management circuit. Automation of plant-level decision-making and removal significantly reduces human labour, increases operational efficiency, and introduces high precision in selective plant management within precision agriculture frameworks.

Keywords: Image processing, Raspberry Pi, Autonomous agricultural system, Plant health detection, DC motor chassis.

1 INTRODUCTION

Precision agriculture has emerged as an effective approach for improving crop productivity while reducing environmental impact through data-driven and site-specific farming practices. The integration of sensing technologies, intelligent decision-making systems, and automation tools has significantly enhanced agricultural efficiency and resource utilization. Recent studies highlight that precision agriculture technologies contribute to optimized input usage, improved crop monitoring, and sustainable farm management practices across diverse agricultural environments [1]. Among the enabling technologies supporting modern precision farming, deep learning and computer vision techniques have gained considerable attention for automated crop monitoring and classification tasks. These approaches facilitate reliable extraction of visual features from field imagery and enable accurate discrimination between crops and weeds under varying environmental conditions. Advanced neural network models have demonstrated strong performance in agricultural image analysis, supporting intelligent decision-making in real-time field operations [2]–[4].

Real-time object detection frameworks such as YOLO have further strengthened vision-based agricultural automation by enabling fast and efficient localization of weeds using low-cost imaging sensors and embedded computing platforms. Such techniques allow continuous monitoring of crop fields and support selective intervention strategies that improve productivity while minimizing unnecessary chemical usage [5]. In addition, vision-based row detection and crop localization techniques have been explored to enhance navigation accuracy and spatial awareness in autonomous agricultural platforms operating under dynamic field conditions [6]. Autonomous robotic systems have also been widely investigated for selective weed control applications. These systems aim to reduce dependence on blanket herbicide spraying and manual labour by enabling targeted removal of unwanted vegetation using intelligent sensing and actuation mechanisms. Robotic weed control platforms provide improved operational efficiency and environmental sustainability compared to conventional weed management practices [7].

Recent developments in machine vision technologies for agricultural robots have further improved the accuracy and reliability of weed detection systems. These advancements support real-time processing capabilities and enable robust operation under challenging field conditions such as varying illumination, background complexity, and plant overlap. Vision-based weeding robots continue to evolve as promising solutions for precision agriculture applications [8], [9]. In parallel, robotic arm technologies have been increasingly integrated into agricultural automation frameworks to support precise manipulation and selective intervention tasks. Such robotic platforms enable accurate positioning and controlled actuation for crop monitoring, harvesting, and weed removal operations. The integration of robotic arms with intelligent perception systems enhances the effectiveness of selective weed control strategies and supports sustainable farming practices [10].

Several automated weed detection and herbicide spraying systems have been developed using embedded controllers and vision-based sensing technologies to improve operational efficiency in agricultural environments. These systems demonstrate the feasibility of integrating image-based detection with mechanical actuation for targeted weed removal tasks [11]. Furthermore, recent advancements in agricultural robotic systems highlight the growing importance of autonomous weeding technologies capable of reducing labour requirements while maintaining high precision and reliability in field-level operations [12]. Despite these developments, challenges remain in achieving seamless integration of real-time vision-based weed detection with precise robotic arm manipulation within compact and cost-effective agricultural platforms. Addressing these challenges is essential for developing efficient autonomous weed management systems that support sustainable precision agriculture practices.

2 Literature Survey

Weed management remains a critical challenge in agricultural production due to its direct impact on crop yield, input utilization efficiency, and environmental sustainability. Precision agriculture technologies have been widely adopted to improve farm productivity through data-driven monitoring and site-specific crop management practices. These technologies enable efficient utilization of fertilizers, water resources, and plant protection measures, thereby supporting sustainable agricultural development [1]. Recent advances in deep learning have significantly improved the capability of agricultural monitoring systems to perform automated crop classification and vegetation analysis. Deep neural network architectures allow automatic extraction of complex visual features from field imagery, enabling reliable crop–weed discrimination under varying environmental conditions. Such approaches have demonstrated strong performance compared with traditional image processing methods in agricultural automation tasks [2].

Fully convolutional neural network architectures have been successfully applied for robust crop and weed detection in precision farming environments. These networks enable pixel-level classification and spatial understanding of agricultural scenes, improving detection accuracy even in complex field conditions involving plant overlap and background variations [3]. Similarly, convolutional neural networks have been used for plant species classification tasks, demonstrating the ability to learn hierarchical representations of vegetation characteristics such as texture, color distribution, and structural patterns [4]. Real-time object detection frameworks such as YOLO have further enhanced the efficiency of automated weed detection systems by enabling fast localization and classification of vegetation targets using embedded platforms. These approaches support practical deployment of intelligent vision-based systems in agricultural environments requiring rapid decision-making and selective intervention [5].

Vision-based crop row detection systems have also been explored to improve navigation accuracy in autonomous agricultural robots. Such techniques assist robotic platforms in maintaining alignment within crop rows, thereby improving operational stability and detection reliability during field traversal [6]. In addition, autonomous robotic weed control systems have been extensively investigated as alternatives to conventional herbicide-based weed management practices. These systems enable selective treatment of weeds while minimizing crop damage and reducing environmental impact [7]. Machine vision technologies continue to play a crucial role in the development of intelligent weeding robots. Recent research highlights the importance of integrating advanced sensing techniques with robust classification algorithms to improve detection accuracy under challenging field conditions such as illumination variability and plant occlusion [8]. Deep learning–based weed detection approaches have further demonstrated improved adaptability and classification performance across different crop types and environmental conditions, supporting reliable deployment of automated agricultural systems [9].

Robotic arm technologies have also been incorporated into agricultural automation frameworks to support precise manipulation and selective intervention tasks. These systems enable accurate positioning and targeted removal of weeds, improving operational efficiency and reducing dependence on manual labour [10]. Embedded controller-based weed detection and herbicide spraying robots have demonstrated the feasibility of integrating image-based detection with automated actuation mechanisms for selective weed control applications [11]. Recent advancements in agricultural robotic systems emphasize the growing importance of autonomous weeding platforms capable of performing reliable detection and removal operations with minimal human intervention. These systems contribute to improved precision agriculture practices by enhancing detection accuracy, reducing chemical usage, and supporting sustainable farming operations [12]. However, despite significant progress in vision-based weed detection and robotic weed control technologies, challenges remain in achieving seamless integration of real-time perception, accurate localization, and precise robotic manipulation within compact and cost-effective agricultural platforms suitable for field deployment.

3 Proposed Method

This paper presents an autonomous vision-driven weed detection and removal system that integrates intelligent perception with robotic actuation for precision agriculture. The system is designed to operate in real-time agricultural field environments, enabling selective weed control while preserving crop integrity. By combining deep learning-based visual analysis, embedded control mechanisms, and robotic manipulation, the proposed framework addresses limitations associated with conventional manual and chemical-based weed management techniques.

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The operational workflow begins with continuous image acquisition using a camera mounted on the mobile robotic platform. Captured field images are transmitted to an embedded processing unit, where preprocessing techniques are applied to enhance visual quality and improve detection reliability. These preprocessing steps include image resizing, noise reduction, and illumination normalization to reduce environmental disturbances such as shadows and uneven lighting conditions. Following preprocessing, refined images are analyzed using a trained convolutional neural network model capable of performing crop–weed discrimination with high reliability. Fig. 1 shows the block diagram of the proposed method.

The CNN automatically extracts hierarchical visual features related to plant texture, structural patterns, and color characteristics, enabling accurate identification of weeds across varying growth stages and background complexities. This learning-based classification approach improves detection performance compared with traditional threshold-based or handcrafted feature extraction techniques. After successful weed identification, spatial coordinates of the detected target within the image frame are determined using the vision processing module. These coordinates are translated into motion control parameters for the robotic arm through a microcontroller-based control interface. Generated control signals are transmitted to the motor driver circuitry, enabling precise positioning of the robotic arm toward the detected weed location. Fig. 2 shows the precision and accuracy graph for existing and proposed model.

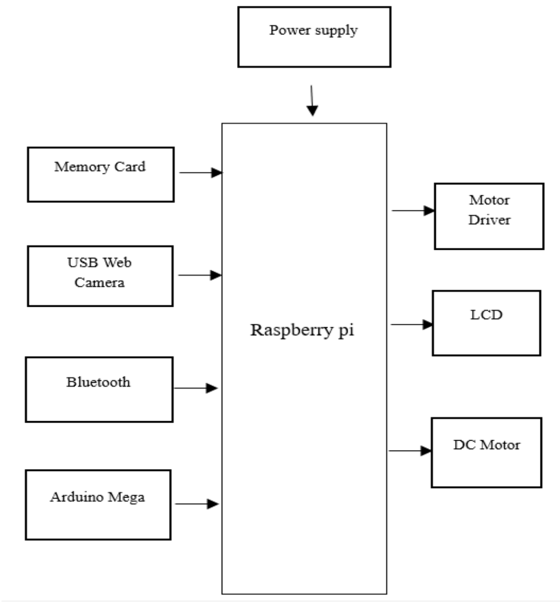

Fig. 1. Block Diagram of Proposed Method

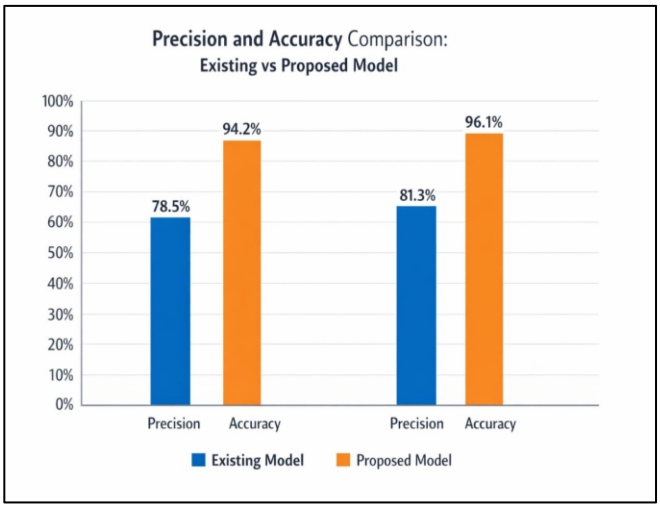

Fig. 2. Precision and Accuracy Graph for Existing and Proposed Model

A mechanical cutting tool or localized spraying mechanism attached to the robotic arm is activated for selective weed removal with minimal disturbance to surrounding crop plants. The robotic actuation system operates in coordination with the perception module to ensure accurate targeting and efficient removal operations within the agricultural environment. Additionally, the system incorporates an IoT-enabled communication interface that supports transmission of operational data to a cloud-based monitoring platform. Detection statistics, execution status information, and performance indicators are periodically uploaded for remote monitoring and analysis. The integration of intelligent visual perception, embedded robotic control, and wireless communication results in an efficient and sustainable weed management solution suitable for precision agriculture applications. Table 1 shows the parameter comparison of the proposed method.

Table. 1 Comparing of existing and proposed model

Parameter	Existing Model	Proposed method
Image Type Used	MS or PAN separately	Fused ms + pan (pansharpened)
Spatial Resolution	Low to Medium	High
Spectral Information	Limited	Rich spectral and spatial details
Detection Method	Manual/Basic image processing	Machine Learning –based classification
Automation Level	Semi -manual	Fully automated
Precision(%)	78.5%	94.2%
Accuracy(%)	81.3%	96.1%
Real- time crop management	Not supported	Supported

4 IMPLEMENTATION

The implementation of the vision-based smart weed detection system focuses on achieving accurate plant discrimination and precise robotic actuation under real agricultural field conditions. The system integrates visual sensing, intelligent classification, and controlled mechanical intervention to support precision agriculture practices with minimal human involvement. A digital RGB camera is rigidly mounted on the agricultural platform to capture continuous field imagery during operation. Camera placement is optimized to maintain consistent coverage of crop rows while reducing occlusion effects and perspective distortion. Captured images are directly forwarded to the embedded processing unit, enabling real-time analysis without reliance on external computational infrastructure. Before classification, acquired images are refined through a sequence of preprocessing operations designed to enhance visual clarity and feature visibility. Image resolution is standardized to balance computational efficiency with preservation of important structural details.

Noise artifacts introduced by environmental variations are reduced using smoothing techniques, while brightness and contrast normalization compensates for illumination variations caused by uneven sunlight conditions. These enhancements improve separation between vegetation regions and background information. Weed identification is performed using a trained convolutional neural network model developed on a dataset containing diverse crop and weed samples. Instead of relying on handcrafted feature extraction techniques, the model automatically learns distinguishing characteristics associated with plant shape, surface texture, and color distribution. During execution, each processed frame is analyzed by the network, which assigns classification labels indicating crop or weed presence along with associated confidence levels. To ensure safe operation during field deployment, a decision logic module evaluates classification confidence values before initiating mechanical actuation. Only detections exceeding a predefined reliability threshold are considered valid weeds.

Spatial positions of confirmed weeds are estimated relative to the robotic arm reference frame, allowing accurate targeting without disturbing surrounding crop plants. The robotic arm operates through a microcontroller-based control unit responsible for translating positional information into joint-level motion commands. Inverse kinematic calculations determine required angular movements for smooth and precise positioning toward detected weed locations. Once alignment is achieved, the end-effector performs localized weed removal either through mechanical cutting action or controlled herbicide application. After completion of each removal operation, the robotic arm returns to its standby configuration to continue subsequent detection cycles. All system components operate within an integrated real-time framework that ensures synchronized communication between vision processing, classification modules, and robotic actuation subsystems. The implemented architecture demonstrates reliable weed detection and targeted removal performance, contributing to reduced chemical usage, decreased labor dependency, and improved operational efficiency in precision agriculture environments.

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5 RESULTS

The performance of the vision-based smart weed detection robotic system for precision agriculture was evaluated through experimental analysis under real-field conditions. System effectiveness was assessed using standard classification and operational performance metrics, including accuracy, precision, recall, F1-score, detection time, and weed removal success rate. Obtained results were compared with conventional image processing–based weed detection approaches to validate performance improvements achieved through the proposed framework. Fig. 3 shows the hardware kit. Simulation code is shown in Fig. 4.

Fig. 3. Hardware Kit

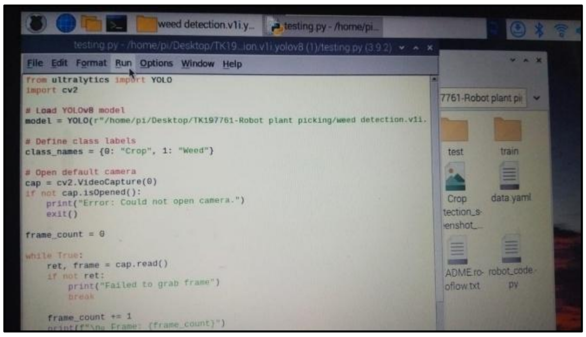

Fig. 4. Simulation

5.1. Quantitative Performance Evaluation

The YOLO-based vision detection framework demonstrated strong classification capability with an overall accuracy of 96.4%, confirming reliable crop–weed discrimination under field conditions. High precision of 95.8% reduced false weed detections, while recall of 96.9% ensured effective identification of weed instances across diverse environmental scenarios. The resulting F1-score of 96.3% indicated balanced and consistent classification performance. Traditional image processing–based detection approaches exhibited comparatively lower accuracy due to dependence on handcrafted feature extraction and sensitivity to illumination variations. Experimental evaluation confirmed that deep learning–based classification significantly improved robustness and detection reliability in complex agricultural environments. Fig. 5 shows the performance metrics comparison graph.

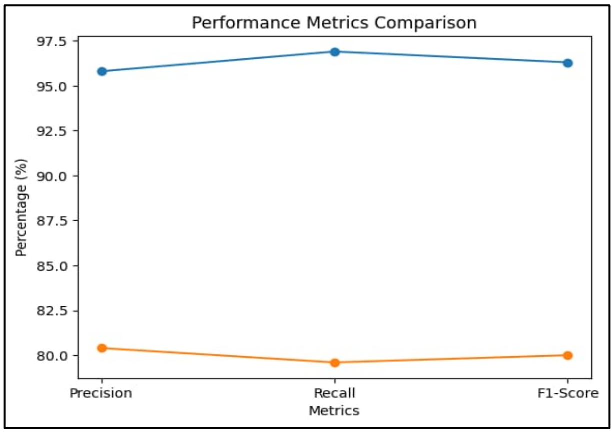

Fig. 5. Performance Metrics Comparison Graph

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Performance metrics obtained during evaluation are summarized below in Table 2.

Table. 2 Performance Evaluation Metrics

Metric	Value
Mean Average Precision (mAP@0.5)	95.6%
Inference Speed	13.84 FPS
Model Memory Footprint	0.012 GB

5.2. Real-Time Detection and Computational Efficiency

Real-time performance is an essential requirement for autonomous agricultural robotic systems operating in dynamic field environments. The implemented detection framework achieved an average weed detection time of 120 ms per frame, which is significantly lower than the 210 ms per frame observed in conventional image processing approaches. This reduction in processing latency enabled smooth navigation and timely actuation of the robotic arm without interruption to field operations. The optimized convolutional neural network architecture combined with an efficient preprocessing pipeline contributed to faster inference performance while maintaining high classification accuracy. Fig. 6 shows the detection of plant. Fig. 7 represents the accuracy comparison of weed detection methods.

Fig. 6. Detection of plant

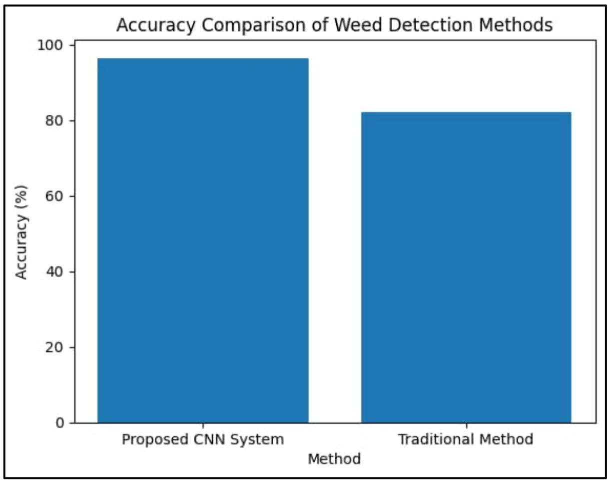

Fig. 7. Accuracy Comparison of Weed Detection Methods

5.3. Robotic Weed Removal Performance

System effectiveness was further validated through integration with a servo-driven robotic arm designed for selective weed removal. Experimental observations indicated a weed removal success rate of 93.5%, demonstrating accurate spatial localization and reliable coordination between perception and actuation modules. The robotic arm selectively targeted unwanted vegetation without disturbing adjacent crop plants, supporting precision agriculture objectives and reducing reliance on chemical herbicide application. This capability confirmed the suitability of the system for environmentally sustainable agricultural operations. Fig. 8 shows the robotic system removing weeds.

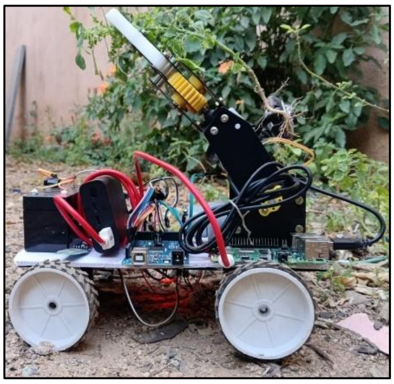

Fig. 8. Robotic system removing weeds

5.4. Discussion

Experimental findings confirmed that the vision-based robotic weed detection system achieved superior performance compared with conventional approaches in terms of detection accuracy, processing speed, and operational reliability. The deep learning–based detection strategy effectively addressed challenges associated with illumination variability, background complexity, and plant overlap commonly encountered in agricultural environments. Integration of intelligent vision processing with autonomous robotic manipulation enabled selective intervention at plant level, supporting scalable and sustainable precision farming practices while improving operational efficiency and reducing chemical usage.

6 CONCLUSION

This paper presented a vision-based smart weed detection robotic arm system designed for precision agriculture through the integration of embedded computing platforms such as Raspberry Pi and Arduino with intelligent sensing modules and deep learning–based visual perception techniques. The system demonstrated the capability to accurately identify weeds and perform selective removal using coordinated robotic manipulation with minimal human intervention. Experimental evaluation confirmed reliable classification performance, efficient real-time detection capability, and effective robotic actuation under agricultural field conditions. The proposed architecture supports reduced chemical herbicide usage, improved operational efficiency, and environmentally sustainable crop management practices, making it suitable for deployment in small- and medium-scale agricultural environments. Future developments in autonomous precision weed control systems can focus on improving real-time performance, robustness, and adaptability under diverse agricultural conditions. Implementation of lightweight deep learning architectures optimized for embedded processing platforms can further enhance detection speed while maintaining classification accuracy. Integration of multiple sensing technologies such as vision sensors, LiDAR, and GPS modules can improve navigation accuracy and perception reliability in complex field environments. Additionally, the development of adaptive weeding mechanisms capable of handling multiple crop varieties and varying soil conditions can increase system versatility. Expansion of large-scale agricultural datasets representing diverse crop types and weed species can further improve model generalization and support reliable deployment across different farming environments.

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This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

REFERENCES

[1] G J. Lowenberg-DeBoer and B. Erickson, "Setting the record straight on precision agriculture adoption," *Agronomy Journal*, vol. 111, no. 4, pp. 1552–1569, May 2019, doi: 10.2134/agronj2018.12.0779.

[2] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, Feb. 2018, doi: 10.1016/j.compag.2018.02.016.

[3] P. Lottes, J. Behley, A. Milioto and C. Stachniss, "Fully Convolutional Networks With Sequential Information for Robust Crop and Weed Detection in Precision Farming," in *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 2870-2877, Oct. 2018, doi: 10.1109/LRA.2018.2846289.

[4] M. Dyrmann, H. Karstoft, and H. S. Midtiby, “Plant species classification using deep convolutional neural network,” *Biosystems Engineering*, vol. 151, pp. 72–80, Sep. 2016, doi: 10.1016/j.biosystemseng.2016.08.024.

[5] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, Real-Time Object Detection,” *arXiv.org*, Jun. 08, 2015. https://arxiv.org/abs/1506.02640

[6] T. Bakker *et al.*, “A vision based row detection system for sugar beet,” *Computers and Electronics in Agriculture*, vol. 60, no. 1, pp. 87–95, Nov. 2007, doi: 10.1016/j.compag.2007.07.006.

[7] D. C. Slaughter, D. K. Giles, and D. Downey, “Autonomous robotic weed control systems: A review,” *Computers and Electronics in Agriculture*, vol. 61, no. 1, pp. 63–78, Sep. 2007, doi: 10.1016/j.compag.2007.05.008.

[8] Y. Li, Z. Guo, F. Shuang, M. Zhang, and X. Li, “Key technologies of machine vision for weeding robots: A review and benchmark,” *Computers and Electronics in Agriculture*, vol. 196, p. 106880, Apr. 2022, doi: 10.1016/j.compag.2022.106880.

[9] H. Zhao and Y. Wang, “Deep learning–based approaches for weed detection in crops,” *Frontiers in Plant Science*, vol. 16, p. 1746406, Jan. 2026, doi: 10.3389/fpls.2025.1746406.

[10] T. Jin and X. Han, “Robotic arms in precision agriculture: A comprehensive review of the technologies, applications, challenges, and future prospects,” *Computers and Electronics in Agriculture*, vol. 221, p. 108938, Apr. 2024, doi: 10.1016/j.compag.2024.108938.

[11] R. Aravind, M. Daman and B. S. Kariyappa, "Design and development of automatic weed detection and smart herbicide sprayer robot," *2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, Trivandrum, India, 2015, pp. 257-261, doi: 10.1109/RAICS.2015.7488424.

[12] C. Lytridis and T. Pachidis, “Recent advances in agricultural robots for automated weeding,” *AgriEngineering*, vol. 6, no. 3, pp. 3279–3296, Sep. 2024, doi: 10.3390/agriengineering6030187.