AI-Driven Sustainable Weed Managing Mobile Robot

Hadi Moeinnia[1], Devin Armstrong[1], Jacob Angelozzi[1], Gavin Theys[1], Kimia Rezaeian[1], Yonghao Wen[1], Devon Scott[1], Emmanuel Sulle[2], and Woo Soo Kim[1]

[1]Simon Fraser University School of Mechatronic Systems Engineering
[2]The Aga Khan University - Tanzania

November 30, 2024

Abstract

This study introduces a compact, autonomous mobile weed management robot designed to promote sustainable agricultural practices and enhance crop protection through effective early-stage weed management. Equipped with a laser-based system, the robot enables precise weed removal tailored to specific agricultural contexts. It employs an AI-driven image classification approach for weed detection, achieving a mean average precision (mAP) of 0.32 and a detection rate of 118 ms on a Raspberry Pi 5 platform. The robot features a two-degree-of-freedom arm for accurate laser positioning, with exposure duration dynamically adjusted based on identified weed species to minimize energy consumption and protect neighboring crops and soil. Field trials in Vancouver, Canada, and Arusha, Tanzania, demonstrated the robot's effectiveness, achieving weed removal success rates of 97% and 96%, respectively, in a maximum of 60 seconds targeting pigweed, purslane, and nutsedge. Designed to be cost-efficient and scalable, this innovative system offers an environmentally sustainable solution for effective weed management, significantly reducing herbicide use and enhancing weed targeting precision. This research underscores the dual benefits of integrating autonomous technology into agriculture, improving productivity and sustainability while protecting crop health and ecosystems.

AI-Driven Sustainable Weed Managing Mobile Robot

Hadi Moeinnia[1], Devin Armstrong[1], Jacob Angelozzi[1], Gavin Theys[1], Kimia Rezaeian[1], Yonghao Wen[1], Devon Scott[1], Emmanuel Sulle[3] and Woo Soo Kim[1, 2*]

[1] Additive Manufacturing Lab, School of Mechatronic Systems Engineering, Simon Fraser University, Surrey, BC, Canada

[2] Global Institute for Agritech, Simon Fraser University, Burnaby, BC, Canada

[3] Arusha Climate and Environmental Research Centre, Aga Khan University, Arusha, Tanzania

Corresponding author email: woosook@sfu.ca

Abstracts

This study introduces a compact, autonomous mobile weed management robot designed to promote sustainable agricultural practices and enhance crop protection through effective early-stage weed management. Equipped with a laser-based system, the robot enables precise weed removal tailored to specific agricultural contexts. It employs an AI-driven image classification approach for weed detection, achieving a mean average precision (mAP) of 0.32 and a detection rate of 118 ms on a Raspberry Pi 5 platform. The robot features a two-degree-of-freedom arm for accurate laser positioning, with exposure duration dynamically adjusted based on identified weed species to minimize energy consumption and protect neighboring crops and soil. Field trials in Vancouver, Canada, and Arusha, Tanzania, demonstrated the robot's

effectiveness, achieving weed removal success rates of 97% and 96%, respectively, in a maximum of 60 seconds targeting pigweed, purslane, and nutsedge. Designed to be cost-efficient and scalable, this innovative system offers an environmentally sustainable solution for effective weed management, significantly reducing herbicide use and enhancing weed targeting precision. This research underscores the dual benefits of integrating autonomous technology into agriculture, improving productivity and sustainability while protecting crop health and ecosystems.Bottom of Form

1. Introduction

1.1. Recent Strategies for Weed Control

The global demand for organic food production is rising rapidly, placing pressure on agricultural systems to increase yields sustainably. Weed control remains a critical aspect of achieving this goal, as weeds compete with crops for essential resources like water, nutrients, and sunlight [1]. Traditional methods, such as manual weeding and herbicide application, are often labor-intensive, environmentally damaging, and contribute to the growing problem of herbicide resistance [2, 5]. Modern techniques enhance traditional weed management by using cover crops to suppress weeds through resource competition [6] and applying integrated weed management (IWM) for long-term control [7]. Strategies for managing herbicide resistance aim to curb the development of resistant weeds [8], while seed destructors, remote sensing, bioherbicides, and drones improve efficiency and sustainability in current practices [9-12].

1.2. Smart Agriculture Opportunities

Recent studies have driven the development of innovative technologies, including smart agriculture and robotics, to optimize weed management practices. Precision agriculture, for example, leverages GPS technology and data analytics to target weed infestations with high accuracy, reducing chemical usage and mitigating harm to non-target plants [13]. Additionally, robotic weeders equipped with cameras and AI algorithms can autonomously identify and remove weeds, decreasing the need for manual labor and herbicides [14]. Smart laser weed control uses laser beams to selectively destroy weeds by heating their tissues, offering a chemical-free and highly precise alternative [15]. Recent advancements in autonomous weeding technologies have shown significant potential for enhancing agricultural efficiency. McCool et al. [16] introduced AgBot II, a system that integrates a camera and lighting module to differentiate between crops and weeds, using either a tine or an arrow hoe for precise, low-impact mechanical weeding. Building on this, Quan et al. [17] developed an intra-row mechanical system with a rotating disk knife, driven by a convolutional neural network (CNN) for accurate weed detection in maize crops. Additionally, Francesco et al. [18] advanced the field by proposing a two-camera system mounted on a four-wheel gantry robot, which refines plant detection and classification. Collectively, these innovations underscore the considerable progress and potential of autonomous systems in agricultural applications. Nonetheless, selectively removing early-stage weeds with laser in small farm fields remains challenging. Additionally, real-time weed detection and species classification using limited computational resources pose further barriers.

This study presents the development of a cost-efficient autonomous robot specifically designed for laser weed control. This robot integrates a low-power laser system with a computer vision platform for real-time weed detection and a two-degree-of-freedom (DoF) robotic arm for precise laser targeting. This approach addresses key challenges in autonomous laser weeding, including accurate weed detection [19], real-time targeting [20], and minimizing energy consumption while ensuring safety [21, 23]. By optimizing laser exposure duration based on weed species and size, we aim to prevent overburn and address potential environmental concerns associated with conventional laser weed control techniques [21].

The operational workflow of the developed compact autonomous weed removal robot is illustrated in Figure 1. To evaluate its effectiveness across diverse invasive species environments, experiments were conducted in both Vancouver, Canada, and Arusha, Tanzania. These locations represent distinct agricultural settings, allowing to assess the robot's adaptability and performance under varying conditions.

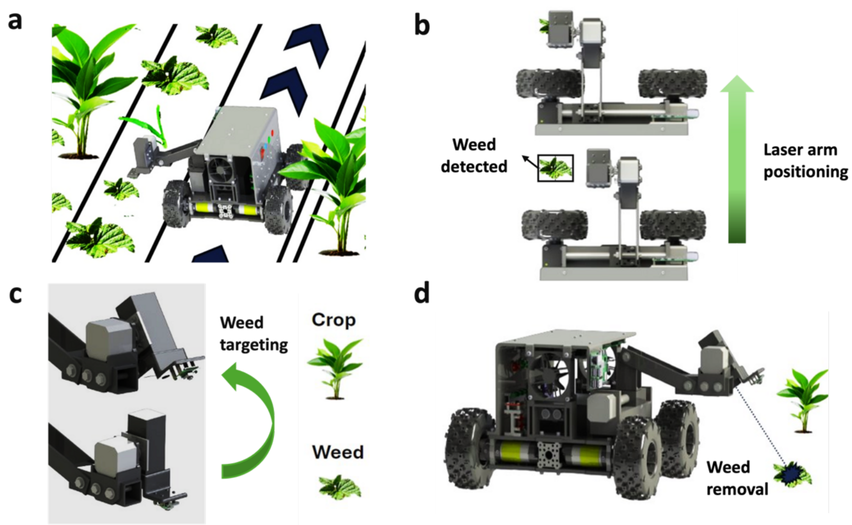

Figure 1. Operational workflow of the compact autonomous weed removal robot. (a) Autonomous navigation and image acquisition along farm pathways. (b) Weed detection and robotic arm repositioning for laser targeting. (c) Precision alignment of the laser through angular mount adjustment. (d) AI-determined laser exposure duration for optimal weed removal.

Materials and methods

2.1. Autonomous mobile robot platform

The weed laser system was integrated onto a goBilda Recon mobile robot chassis, providing a robust foundation for autonomous operation. A custom-designed, 3D-printed PLA frame was fabricated to ensure structural integrity and stability during operation. An adjustable two-degree-of-freedom (DoF) robotic arm, responsible for manipulating the laser, was incorporated into the chassis assembly (Figure 2a, b). The laser and camera were co-mounted on a shared bracket, maintaining a fixed relative position and orientation to facilitate precise synchronization during weed detection and removal processes (Figure 2c).

The mobile robot platform is driven by four brushed DC motors (312 RPM) with 537.7 PPR encoder resolution, enabling accurate locomotion control. Two stepper motors (12V, 0.33A, 0.23Nm, NEMA17 standard) were employed for actuating the weed removal robotic arm. The STM32F439 Nucleo-144 board, featuring an STM32F4 ARM® Cortex®-M4 32-bit MCU, served as the microcontroller, handling the locomotion control of the mobile robot. Adafruit 4007 ultrasonic sensors were positioned on the sides of the robot for collision avoidance. Additionally, an ICM-20948 9DOF IMU Breakout Board was used to measure the speed, acceleration, and orientation of the mobile platform (Figure S1).

A 12V 30Ah Lithium Iron Phosphate ($LiFePO_4$) battery with a 30A Battery Management System (BMS) powers the robot, providing an operational duration exceeding three hours. To maintain the battery temperature within its optimal operating range, two 80mm x 80mm

12VDC fans were installed at the front and rear of the chassis to facilitate airflow within the battery compartment. A 12V blue diode laser engraver with a wavelength of 450 nm and a 4 Watt optical laser output was utilized for weed removal, chosen for its compact, portable design and its capability to deliver precise thermal energy to targeted weeds. The distance between the laser lens and the target was maintained at 5-10 cm to ensure optimal optical performance. The duration of laser exposure is modulated based on the identified weed species and its size, using empirical data from preliminary trials on the time required to induce complete necrosis.

The autonomous robot initiates its operation by traversing the field at a controlled speed of 5 cm/s along a straight path. This designated speed facilitates comprehensive terrain scanning and allows sufficient time for real-time weed detection. To optimize computational resources, the robotic arm is activated for precise weed targeting and removal only after a weed is detected. Upon positive identification of a weed within the camera's field of view, the robot attempts to realign itself by referencing the history of wheel encoder values before pausing its locomotion. This ensures that the robot moves back to the encoder value recorded at the time the image was captured before stopping. The integrated linear actuator then positions the laser arm, aligning it with the centroid of the detected weed's bounding box (Figure 3b).

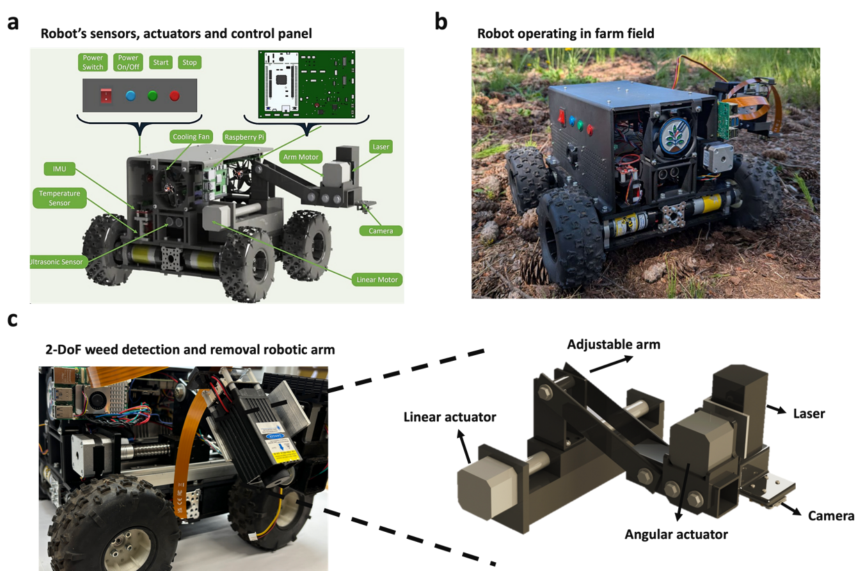

Figure 2. Autonomous weed removal robot platform. (a) Assembled robot with labeled components. (b) Illustration of the robot operating in a farm field environment. (c) Close-up view of the adjustable robotic arm used for weed detection and laser targeting.

2.2. Real-time weed detection and removal

Real-time video recording was achieved using a Sony IMX708 camera, configured with a resolution of 11.9 megapixels, a 102-degree horizontal field of view, and a 67-degree vertical field of view. Video processing was subsequently performed on a Raspberry Pi 5, equipped with a 2.4 GHz quad-core 64-bit Arm Cortex-A76 CPU, 512 KB per-core L2 cache, a 2 MB shared L3 cache, and 8 GB of memory. This configuration provided a cost-effective computational solution for real-time weed detection. To reduce processing time, a preprocessing stage was implemented to filter video frames based on green pixel density. This approach prioritized frames likely containing vegetation (i.e., those with more than 50% green pixels), thus focusing computational resources on potential weed regions and reducing unnecessary processing of bare ground areas (Figure 3a). For weed detection and classification, the You Only Look Once X (YOLOX) architecture was used. This anchor-free architecture employs a backbone, neck, and head structure to perform feature extraction, feature aggregation, and bounding box prediction, respectively [25]. The YOLOX architecture was chosen over YOLO models for improved speed and accuracy. Two versions of the YOLOX object detection architecture, YOLOX-s and YOLOX-nano were used for training and comparison.

A dataset of approximately 10,000 weed images was created for training by augmenting 541 raw images of three weed types—pigweed, purslane, and nutsedge—using the OpenCV library (Figure S3a). Roboflow software was used for image annotation and data preparation (Figure S3b). The dataset was split into 70% training, 20% validation, and 10% test data in VOC Pascal format prior to training. The image input size was set to 640 x 640 for YOLOX-s and 416 x 416 for YOLOX-nano.

The training process was performed on a computer with a 13th Gen Intel Core i9-13900k 3.00 GHz processor, augmented by an NVIDIA GeForce RTX 3080 and 128 GB RAM, taking approximately two days to complete. The trained YOLOX model detects, classifies, and creates a bounding box around the detected weed. The center of the predicted bounding box is then calculated for precise positioning and targeting by the robot's laser arm (Figure 3b).

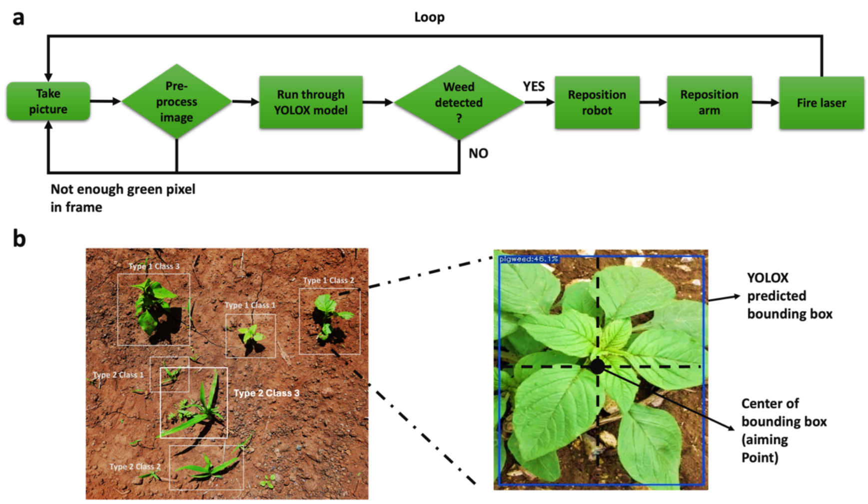

Figure 3. Weed detection and laser targeting. (a) Flowchart of the algorithm for weed detection and automated laser targeting. (b) Visualization of the weed detection and laser targeting process. The YOLOX model generates a bounding box around the identified weed, and the laser is automatically directed to the center of this box.

Results and discussion

Thermal laser performance on weed removal

Field trials were conducted to evaluate the efficacy of the laser weed removal system. Three distinct size groups of Nutsedge and Pigweed, and two size groups of Purslane—common weed species in the Arusha and Vancouver areas—were included in the trials (Table 1).

Table 1: Weed Species and Size Classifications

Weed Type	Group Size	dimensions (cm x cm)	Group Size	dimensions (cm x cm)	Group Size	dime
Pigweed	Small	1.5 x 1.5	Medium	3 x 3	Large	4.5 x

Weed Type	Group Size	dimensions (cm x cm)	Group Size	dimensions (cm x cm)	Group Size	dime
Nutsedge	Small	1.5 x 1.5	Medium	3 x 3	Large	4.5 x
Purslane	Small	1.5 x 1.5	Medium	3 x 3	N/A	N/A

The laser weed removal process involves two distinct stages:

Smoking: Visible emission of smoke from the targeted plant tissue, indicating the initial effects of laser energy.

Perishing: Complete death of the weed, signifying successful removal.

Successful weed removal was defined as the weed exhibiting both stages—smoking and perishing—within a 60-second timeframe. This temporal constraint enhances the speed, safety, and energy efficiency of the autonomous weed removal robot. The laser exposure duration required for effective weed removal was found to depend on both the weed species and its size. To determine optimal exposure times, field experiments were conducted in Arusha, Tanzania, and Vancouver, Canada, during sunny summer conditions, as both locations have comparable average relative humidity levels (approximately 70%).

The resulting data, detailing the time to smoking and time to perishing for various weed species and size groups, are presented in Figure 4. A one-way analysis of variance (ANOVA) was performed to examine the influence of weed species on these observed durations. The ANOVA results revealed significant differences ($p < 0.05$) in smoking and perishing times with respect to weed species, except for the smoking time of large-sized Nutsedge and Pigweed ($p = 0.40$). As expected, larger weeds required longer exposure times to achieve both smoking and perishing. The average perishing time remained under 30 seconds in all experiments, except for large Pigweeds, which had an average perishing time of 44.5 seconds. These findings underscore the system's robustness to environmental variations and its effectiveness across a diverse range of weed species, supporting the strategy of tuning laser exposure times based on weed species and size (Figure S2).

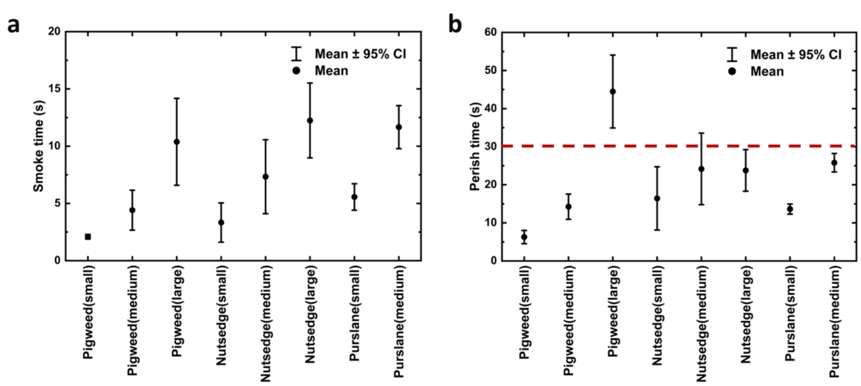

Figure 4. Laser exposure duration required for weed removal. *(a) Time required to initiate smoking in three weed species across different size classes. (b) Time required to achieve complete perishing in three weed species across different size classes.*

Object detection and classification

To optimize the balance between real-time performance and detection precision, the open-sourced AI machine learning tool, YOLOXs: YOLOX-s and YOLOX-nano, were trained and evaluated. The Intersection over Union (IoU) and confidence threshold parameters were tuned within a range of 0.4 to 0.7 to maximize the mean average precision (mAP) of the YOLOX models (see Figure S4).

The performance of the YOLOX models was evaluated in two scenarios: object detection and classification. Confusion matrices for weed detection using YOLOX-nano and YOLOX-s are shown in Figures 5a and 5d, respectively. A comparison of weed true labels against None-predicted labels highlights the enhanced capability of the YOLOX-s model in detecting weeds that YOLOX-nano fails to detect. Furthermore, YOLOX-s achieved 13% and 16% higher accuracy in correctly detecting Nutsedge and Pigweed, respectively, albeit with a 7% reduction in accuracy for Purslane detection. Both models demonstrated high accuracy in classifying weed species, with YOLOX-nano showing a slight advantage over YOLOX-s in classifying Purslane (Figures 5b and 5e).

YOLOX model weights were saved every 10 epochs during training to enable resumption in case of interruptions. The convergence of total training loss for each model, shown in Figures 5c and 5f, indicates that YOLOX-nano and YOLOX-s reach loss values of 1 and 2.5 after 50,000 and 28,000 training iterations, respectively (Figures 5 c and f). The sudden increase in total loss observed in the YOLOX-s training process at step 15,000 (Figure 5f) resulted from resuming training with saved weights after an interruption.

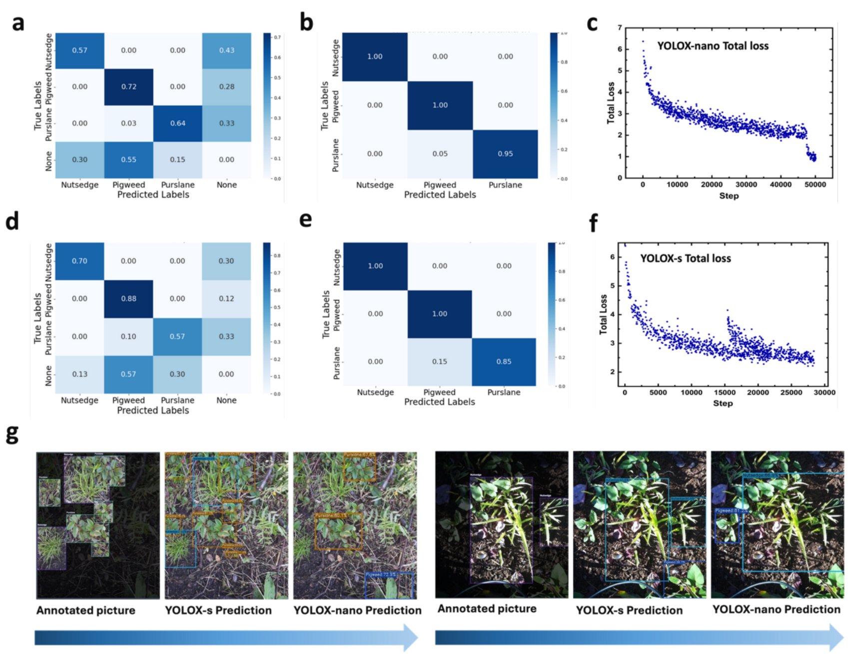

Figure 5: Performance Evaluation of YOLOX Models. (a) Confusion matrix for object detection using YOLOX-nano (b) Confusion matrix for classification using YOLOX-nano (c) Total training loss for YOLOX-nano (d) Confusion matrix for object detection using YOLOX-s (e) Confusion matrix for classification using YOLOX-s (f) Total training loss for YOLOX-s (g) Comparative analysis of YOLOX-s and YOLOX-nano performance in weed detection and classification.

Conclusion

The integration of an AI-driven weed management robot presents a compelling solution for sustainable agriculture, particularly in early-stage weed removal and crop protection. By employing a low-power thermal laser system, this innovative robot can effectively target and eliminate major weeds such as nutsedge, pigweed, and purslane, which significantly contribute to crop yield losses. Field trials in diverse environments like Vancouver, Canada, and Arusha, Tanzania, have showcased the robot's remarkable effectiveness, achieving weed removal success rates of 97% and 96%, respectively. This high level of efficiency not only underscores the robot's capability to adapt to various agronomic conditions but also highlights its potential for reducing reliance on chemical herbicides, thereby promoting a more sustainable farming approach.

The implementation of a preprocessing step that filters video frames based on green pixel density is critical for enhancing computational efficiency. By concentrating processing power on areas with a higher likelihood of weed presence, the system can operate more swiftly and focus on significant tasks, minimizing resource use and processing time. For the task of weed detection and classification, two advanced AI algorithms were evaluated. One algorithm demonstrated higher accuracy in identifying weeds, while the other offered superior real-time performance, making it more suitable for integration into the robot's operational algorithm. This strategic choice ensured an effective balance between detection accuracy and processing speed, which is crucial for timely weed intervention in dynamic field conditions. YOLOX-s provided a higher mean Average Precision (mAP) of 0.44, indicating its accuracy in identifying weeds. However, the selection of YOLOX-nano for integration into the robot's operational algorithm was strategic; its superior real-time performance—achieving a processing time of just 118.02 ms on the Raspberry Pi 5 platform—ensures that the robot can respond promptly in dynamic field conditions. This speed is crucial for timely weed intervention, which can significantly influence the overall success of crop management efforts. Thus, the deployment of this AI-driven weed management robot is not only a step towards enhanced weed control but also supports sustainable agricultural practices. By minimizing the need for chemical applications and leveraging advanced detection and response technologies, farmers can achieve effective weed management while enhancing the health of ecosystems and promoting biodiversity. Thermal lasers we used here can effectively manage pests and weeds, but they may also harm food crops and soil by causing crop damage, altering the soil microbiome, and affecting nutrient availability. To mitigate these risks, careful calibration of laser intensity is essential. Engaging agricultural experts and future investigations ensure the safe and sustainable use of thermal lasers in agriculture.

Table 2: Comparison between the performance of YOLOX-s and YOLOX-nano models on Raspberry pi

Model	Mean Average Precision (mAP)	Speed (ms)	Model size (MB)
YOLOX-nano	**0.32**	**118.02**	**3.62**
YOLOX-s	**0.44**	**1540.08**	**35.75**

Author contributions

Woo Soo Kim conceived the concept for the compact autonomous weed management robot and supervised the project. Hadi Moeinnia supported the team in the robot's design and development, oversaw field experiments, completed YOLOX weed detection tasks, and conducted data analysis. Devin Armstrong was responsible for software development, focusing on weed targeting and laser arm control. Jacob Angelozzi managed the MCU programming for the robot's autonomous locomotion. Gavin handled the mechanical design and implementation of the chassis and laser arm, in addition to manufacturing components. Kimia Rezaeian led the electrical design and implementation of the robot. Yonghao Wen and Devon Scott worked on the implementation of real-time object detection. Emmanuel Sulle coordinated the field validation of the robot's performance conducted in Arusha, Tanzania. All authors contributed to drafting the manuscript and preparing figures, tables, and datasets.

Acknowledgments

The authors acknowledge the philanthropic contribution from the Jenabai Hussainali Shariff Family for the *field trip of the authors to the Arusha Climate and Environmental Research Centre in Tanzania. Also, authors acknowledge the financial support from the Natural Sciences and Engineering Research Council of Canada (NSERC) with the Discovery Grant RGPIN-2023-03455.*

Competing interests

All authors declare no financial or non-financial competing interests.

References

1. Nagargade M, Singh MK, Tyagi V, Govindasamy P, Choudhary AK, Rajpoot K, et al. Ecological weed management and square planting influenced the weed management, and crop productivity in direct-seeded rice. Scientific Reports 2024, 14(1):10356, https://doi.org/10.1038/s41598-024-56945-y.

2. Nichols V, Verhulst N, Cox R, Govaerts B. Weed dynamics and conservation agriculture principles: A review. Field Crops Research 2015, 183:56–68, https://doi.org/10.1016/j.fcr.2015.07.012.

3. Hussain M, Farooq S, Merfield C, Jabran K. Mechanical Weed Control. Non-Chemical Weed Control, 2018. page 133–55, https://doi.org/10.1016/B978-0-12-809881-3.00008-5.

4. Radhakrishnan R, Alqarawi AA, Abd_Allah EF. Bioherbicides: Current knowledge on weed control mechanism. Ecotoxicol Environ Saf 2018, 158:131–8, https://doi.org/10.1016/j.ecoenv.2018.04.018.

5. Gerhards R, Andújar Sanchez D, Hamouz P, Peteinatos GG, Christensen S, Fernandez-Quintanilla C. Advances in site-specific weed management in agriculture—A review. Weed Research 2022, 62(2):123–33, https://doi.org/10.1111/wre.12526.

6. Westwood JH, Charudattan R, Duke SO, Fennimore SA, Marrone P, Slaughter DC, et al. Weed Management in 2050: Perspectives on the Future of Weed Science. Weed Science 2018, 66(3):275–85, https://doi.org/10.1017/wsc.2017.78.

7. Chandra Pandey P, Tripathi AK, Sharma JK. An evaluation of GPS opportunity in market for precision agriculture. GPS and GNSS Technology in Geosciences. Elsevier; 2021. page 337–49, https://doi.org/10.1016/B978-0-12-818617-6.00016-0.

8. Zhang, W., Miao, Z., Li, N. *et al.* Review of Current Robotic Approaches for Precision Weed Management. *Current Robotic Reports* 3, 139–151 (2022), https://doi.org/10.1007/s43154-022-00086-5.

9. Bauer M V., Marx C, Bauer F V., Flury DM, Ripken T, Streit B. Thermal weed control technologies for conservation agriculture—a review. Weed Research 2020, 60(4):241–50, https://doi.org/10.1111/wre.12418.

10. Scavo A, Fontanazza S, Restuccia A, Pesce GR, Abbate C, Mauromicale G. The role of cover crops in improving soil fertility and plant nutritional status in temperate climates. A review. Agronomy for Sustainable Development 2022, 42(5):93, https://doi.org/10.1007/s13593-022-00825-0.

11. Scavo A, Mauromicale G. Integrated Weed Management in Herbaceous Field Crops. Agronomy 2020, 10(4):466, https://doi.org/10.3390/agronomy10040466.

12. Beckie HJ, Ashworth MB, Flower KC. Herbicide Resistance Management: Recent Developments and Trends. Plants 2019, 8(6):161, https://doi.org/10.3390/plants8060161.

13. Esposito M, Crimaldi M, Cirillo V, Sarghini F, Maggio A. Drone and sensor technology for sustainable weed management: a review. Chemical and Biological Technologies in Agriculture

2021, 8(1):18, https://doi.org/10.1186/s40538-021-00217-8.

14. Hasan M, Ahmad-Hamdani MS, Rosli AM, Hamdan H. Bioherbicides: An Eco-Friendly Tool for Sustainable Weed Management. Plants 2021, 10(6):1212, https://doi.org/10.3390/plants10061212.

15. Roslim MHM, Juraimi AS, Che'Ya NN, Sulaiman N, Manaf MNHA, Ramli Z, et al. Using Remote Sensing and an Unmanned Aerial System for Weed Management in Agricultural Crops: A Review. Agronomy 2021, 11(9):1809, https://doi.org/10.3390/agronomy11091809.

16. Borger CPD, Riethmuller GP, Renton M. Weed Seed Wizard: A tool that demonstrates the value of integrated weed management tactics such as harvest weed seed destruction. Computers and Electronics in Agriculture 2018, 147:27–33, https://doi.org/10.1016/j.compag.2018.02.011.

17. McCool CS, Beattie J, Firn J, Lehnert C, Kulk J, Bawden O, et al. Efficacy of Mechanical Weeding Tools: a study into alternative weed management strategies enabled by robotics. IEEE Robotics and Automation Letters 2018, 1–1, https://doi.org/10.1109/LRA.2018.2794619.

18. Quan L, Jiang W, Li H, Li H, Wang Q, Chen L. Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode. Biosystems Engineering 2022, 216:13–31, https://doi.org/10.1016/j.biosystemseng.2022.01.019.

19. Visentin F, Cremasco S, Sozzi M, Signorini L, Signorini M, Marinello F, et al. A mixed-autonomous robotic platform for intra-row and inter-row weed removal for precision agriculture. Computers and Electronics in Agriculture 2023, 214:108270, https://doi.org/10.1016/j.compag.2023.108270.

20. Li Y, Guo Z, Shuang F, Zhang M, Li X. Key technologies of machine vision for weeding robots: A review and benchmark. Computers and Electronics in Agriculture 2022, 196:106880, https://doi.org/10.1016/j.compag.2022.106880.

21. Wang A, Zhang W, Wei X. A review on weed detection using ground-based machine vision and image processing techniques. Computers and Electronics in Agriculture 2019, 158:226–40, https://doi.org/10.1016/j.compag.2019.02.005.

22. Andreasen, C., Vlassi, E. & Salehan, N. Laser weeding: opportunities and challenges for couch grass (Elymus repens (L.) Gould) control. Scientific Reports 2024, https://doi.org/10.1038/s41598-024-61742-8.

23. Merfield CN. Robotic weeding's false dawn? Ten requirements for fully autonomous mechanical weed management. Weed Research 2016, 56(5):340–4, https://doi.org/10.1111/wre.12217.

24. Andreasen C, Scholle K, Saberi M. Laser Weeding with Small Autonomous Vehicles: Friends or Foes? Frontiers in Agronomy 2022, 4, https://doi.org/10.3389/fagro.2022.841086.

25. Ge Z, Liu S, Wang F, Li Z, Sun J. YOLOX: Exceeding YOLO Series in 2021. ArXiv [Web references] 2021, abs/2107.08430. Available from: https://api.semanticscholar.org/CorpusID:236088010.