



Weed Detection and Killing Using Laser Beam

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Abstract- Manual weeding is labour-intensive, and chemical herbicides carry well-documented risks of soil contamination, herbicide-resistant weed populations, and residue in food crops. Laser-based weed control has emerged as a non-chemical alternative in which a focused beam irradiates a weed's apical meristem, using thermal energy to destroy the growth centre without disturbing the soil. This paper presents the design of an autonomous weed detection and laser-killing system that combines an RGB/NIR camera, a convolutional neural network (CNN) for real-time crop-weed discrimination, a galvanometer-steered laser module for meristem targeting, and a closed-loop verification step that re-images the treated area to confirm the outcome. The system is designed around two literature-grounded design choices: attribute-level targeting of the meristem, which the literature identifies as the most energy-efficient kill point, and a species- and stem-diameter-aware dose controller, since required laser energy varies substantially with plant morphology. Because this system is at the design stage and has not yet been field-deployed, its evaluation combines literature-reported figures from six recent laser-weeding studies with explicit design targets for detection accuracy, kill efficacy, and processing speed, so that a future prototype can be benchmarked directly against both.

Keywords- Laser Weeding · Weed Detection · Precision Agriculture · Convolutional Neural Network (CNN) · YOLO · Meristem Targeting · Non-Chemical Weed Control · Autonomous Robotics · Computer Vision

I. INTRODUCTION

Weeds compete with crops for light, nutrients, and water, and left unmanaged can substantially reduce yield and quality. The two dominant control methods today — manual/mechanical weeding and chemical herbicide application — each carry a well-documented cost: manual and mechanical methods are labour-intensive and, in the mechanical case, disturb the soil, while herbicides face growing restriction due to herbicide-resistant weed populations, groundwater contamination, and consumer preference for chemical-free produce. Laser-based weed control has been investigated since the early 2000s as a third path: a focused beam of light is aimed at a weed's apical meristem, and the resulting thermal energy causes irreversible cell damage in the growth centre, killing or severely stunting the plant without any chemical input or soil disturbance.

Recent advances in real-time object detection (particularly the YOLO family of CNNs) and in compact, precisely steerable diode and fiber lasers have made autonomous, camera-guided laser weeding practical rather than purely experimental, and commercial units are now being field-tested against herbicides with favourable results [3]. This paper proposes an autonomous weed detection and killing system that pairs a CNN-based crop-weed classifier with a galvanometer-steered laser module



targeting the apical meristem, and defines an evaluation plan grounded in the specific figures reported by the six most closely related studies surveyed in Section 3.

The specific contributions of this work are:

- An end-to-end pipeline design — sensing, CNN-based detection, meristem localization, beam steering, dose control, and post-treatment verification — with an explicit feedback loop rather than open-loop firing.
- A dose-control strategy that adjusts laser power and exposure time by weed species and stem diameter, directly informed by the dose–response literature [5], [6], rather than applying a fixed energy dose to every weed.
- A literature-grounded evaluation framework, comparing the proposed design's targets against six recent laser-weeding studies on the same metrics (detection accuracy, kill efficacy, processing speed, energy per weed) rather than presenting targets in isolation.

II. PROBLEM STATEMENT AND OBJECTIVES

Existing weed control practice suffers from three linked weaknesses: manual and mechanical weeding do not scale to large field areas without substantial labour cost; herbicide application, while scalable, is under increasing regulatory and ecological pressure and cannot selectively spare individual plants at sub-centimetre precision; and early laser-weeding systems, where autonomous, have generally optimized detection accuracy or kill efficacy in isolation rather than as a single evaluated pipeline (Section 3). This motivates the following objectives: (i) to design a CNN-based system that reliably distinguishes crop from weed in real time; (ii) to localize the weed's apical meristem in 3D so the laser can be aimed precisely; (iii) to control laser dose by species and stem diameter rather than a fixed setting; (iv) to verify treatment outcome via re-imaging rather than assuming a single pass is sufficient; and (v) to enforce a safety interlock that prevents firing when crop/weed confidence is low or a foreign object is detected nearby.

III. LITERATURE SURVEY

Table I summarizes six recent studies most directly relevant to CNN-guided laser weed control, spanning system-level robots, static laser-weeding platforms, commercial field trials, modular actuation design, and the underlying laser–plant dose–response physics.

Table 1. Summary of Literature Survey on Cnn-Guided and Laser-Based Weed Control

Author(s)/Year	Method Used	Key Contribution	Limitation
Mwitta, Rains & Prostko (2024)	Autonomous diode-laser weeding robot, cotton field: stereo vision + YOLOv4-tiny + pan-tilt laser	Real-time detection at 52 fps on embedded hardware; validated on an autonomous mobile platform	Evaluated in a single crop context; YOLOv4-tiny is ~4.7% less precise than full YOLOv4
Du, Li, Duan, Hua & Hu (2024)	Static laser weeder; RGB+NIR image fusion with improved YOLOv8 (Swin-transformer + Slim-neck)	Model mAP of 96.0%; demonstrates fusion improves imaging in complex backgrounds	End-to-end field detection accuracy (82.1%) and laser efficiency (72.3%) well below model mAP



Sosnoskie et al. (2025)	Field trial of a commercial autonomous laser weeder vs. herbicides, three vegetable crops	$\geq 97\%$ weed-biomass reduction; $\geq 30\%$ crop-growth increase; $> 90\%$ weed control, per pass	Proprietary system (laser power/wavelength undisclosed); manually tuned by a field engineer
Blanco, Emmi & Fernández (2025)	Modular robotized laser module design for Agriculture 4.0	Proposes a modular, autonomous laser-actuation architecture decoupled from any single platform	Module-level contribution; integrated field-scale validation not yet reported
Wöltjen, Haferkamp, Rath & Herzog (2008)	CO ₂ (10.6 μm) and diode (940 nm) laser irradiation of the apical meristem, dose-response study	Established ED90 dose-response models for meristem-targeted laser kill across species	Laboratory-controlled, hand-positioned laser; no autonomous detection or targeting pipeline
Lati et al. (2026)	Comparative evaluation of a 1940-nm fiber laser against CO ₂ and diode systems	Shows CO ₂ needs less energy ($\sim 1 \text{ J mm}^{-2}$) than diode ($\sim 3 \text{ J mm}^{-2}$) for 90% control (ED90)	Energy-efficiency findings are lab-based; do not include a full detection-and-targeting pipeline

Across this literature, two consistent patterns emerge. First, model-level detection accuracy (e.g., 96.0% mAP [2]) is consistently higher than end-to-end, in-field system accuracy (82.1% [2]) and kill efficacy (72.3%–97% [2], [3]), which motivates evaluating the full pipeline in Section 7 rather than the CNN in isolation. Second, laser wavelength and dose selection matter as much as detection accuracy: CO₂ lasers require roughly a third of the energy of diode lasers for the same 90% control outcome [6], but diode and fiber lasers are more compact and field-practical [6], [9] — a trade-off the proposed dose controller (Section 6) is designed to manage per species rather than resolve with one fixed laser type.

IV. PROPOSED SYSTEM DESIGN

1. High-Level Design

A mobile platform carries an RGB/NIR (or stereo) camera over the crop row. A CNN classifier distinguishes crop from weed and localizes each detected weed's apical meristem in 3D. A galvanometer-steered mirror aims a diode or fiber laser at the meristem, and a dose controller sets power and exposure time from the weed's species and estimated stem diameter. After firing, the camera re-images the treated spot to verify the outcome and log it, closing the loop for the next pass.

2. Module-Wise Design

- Sensing Module — RGB/NIR or stereo camera mounted ahead of the laser assembly, streaming frames of the crop row.
- Detection & Classification Module — YOLOv8-based CNN performing real-time crop-weed discrimination.
- Meristem Localization Module — combines 2D centroid estimation with depth data to compute 3D targeting coordinates.



- Beam-Steering Module — galvanometer mirror / pan-tilt mechanism that aims the laser at the localized meristem.
- Dose-Control Module — sets laser power and exposure time from species and stem-diameter estimates, following published dose-response curves [5], [6].
- Verification & Safety Module — re-images the treated spot to confirm the outcome, and halts firing if crop/weed confidence is low or an object is detected too close to the beam path.

V. SYSTEM ARCHITECTURE

Fig. 1 illustrates the proposed pipeline. Frames from the sensing module feed the detection and classification stage, whose output (bounding boxes and species labels) feeds meristem localization. The beam-steering and dose controllers then act together to fire the laser at the correct 3D position with a species-appropriate energy dose. The verification stage closes the loop back to the sensing module, and a safety interlock gates every firing decision independently of the detection confidence returned by the CNN.

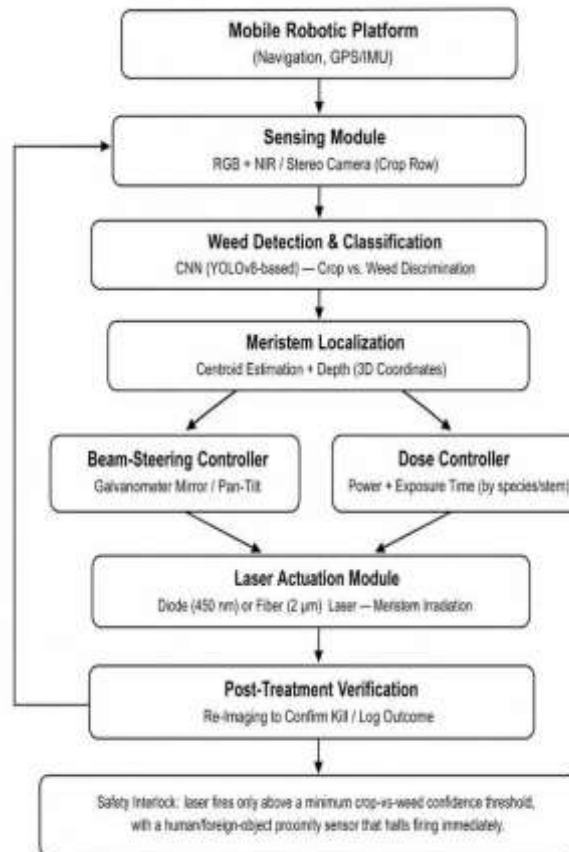


Fig. 1. End-to-end processing pipeline of the proposed weed detection and laser-killing system.

VI. METHODOLOGY: ALGORITHMS AND TECHNOLOGIES

1. Detection and Localization

- CNN architecture: YOLOv8 (or a lighter YOLOv4-tiny variant for embedded deployment), optionally fused with NIR imagery to improve detection in cluttered backgrounds [2].



- Depth estimation: stereo camera pair or an RGB-D sensor, providing the 3D coordinate needed for accurate beam aiming [1].

2. Laser Targeting and Dosing

- Beam steering: galvanometer mirrors or a pan-tilt mount, directing the beam to the meristem coordinate with millisecond-scale response.
- Laser source: diode laser (~450–940 nm) for compactness and cost, or fiber laser (~2 μm) for higher energy-transfer efficiency into plant tissue where higher throughput is required [6], [9].
- Dose control: exposure time and power set per species and estimated stem diameter, following ED90 dose-response curves established in the literature [5], [6].

3. Control Software and Safety

- Real-time control implemented over ROS (Robot Operating System), coordinating the sensing, detection, targeting, and firing stages as a finite state machine [1].
- Safety interlock: firing is disabled below a minimum crop/weed confidence threshold and immediately halted by a proximity sensor if a person or foreign object enters the beam path.

In operation, each detected weed passes through localization, dose selection, beam steering, and firing before the same region is re-imaged to confirm treatment; if the check fails, the weed is queued for re-treatment on a subsequent pass rather than assumed dead after one exposure.

VII. RESULTS AND PERFORMANCE EVALUATION

Because the system described here is at the design stage, this section compares design targets against the specific figures reported by the six studies in Table I, rather than presenting standalone claims. Figures marked “target” are architectural design goals to be confirmed once a working prototype is field-tested.

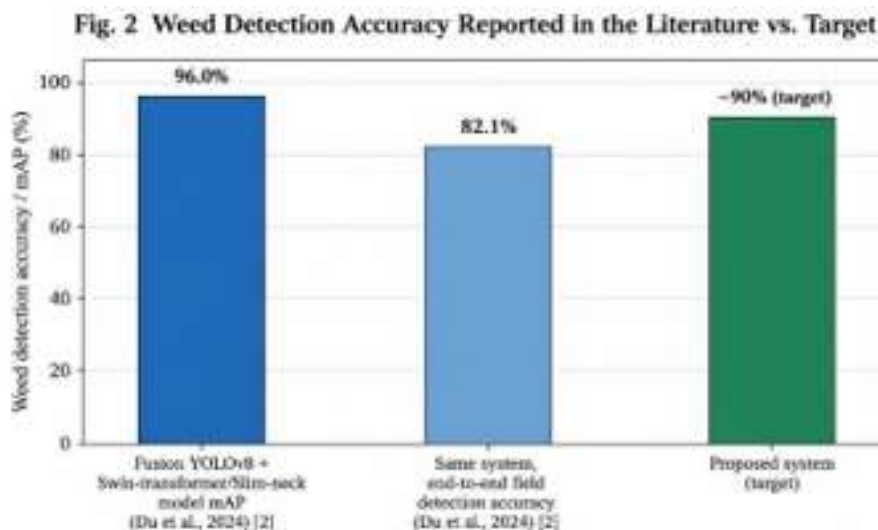


Fig. 2. Weed detection accuracy: model-level mAP vs. end-to-end field accuracy reported in the literature, against the proposed system's target.

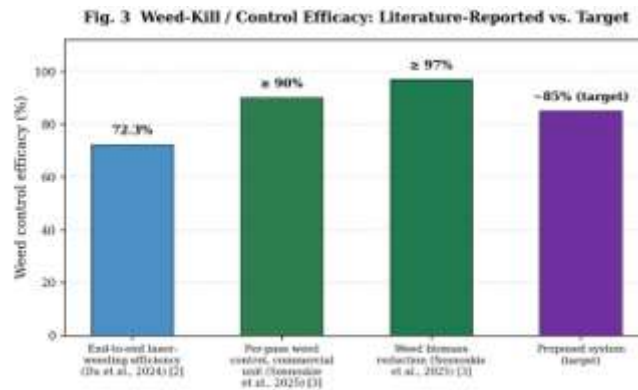


Fig. 3. Weed-kill / control efficacy reported across three literature sources, against the proposed system's target.

The detection-accuracy target (Fig. 2) is set below the fusion model's 96.0% mAP but above its 82.1% field accuracy [2], reflecting the expectation that RGB+NIR fusion and a stereo depth channel improve on a single-model baseline without matching a controlled benchmark's mAP. The kill-efficacy target (Fig. 3) is set below the commercial Carbon Robotics figures [3], since that system's proprietary laser power and tuning by a field engineer are not assumed to be matched by a first prototype, and above the 72.3% end-to-end figure reported for a comparable open academic system [2]. Table II summarizes all indicators, including energy-per-weed figures, which show close to a six-fold difference between the most and least energy-efficient wavelength/power combinations reported in the literature [6] — the reason the proposed dose controller is species- and diameter-aware rather than fixed.

Table 2. Summary of Performance Indicators Used to Evaluate the Proposed System

Metric	Reference value (literature)	Proposed system
Weed detection accuracy (field)	82.1–96.0% (model mAP vs. field accuracy) [2]	~90% (target)
Weed control / kill efficacy	72.3–97% depending on system and crop [2], [3]	~85% (target)
Detection inference speed	52 fps, embedded hardware [1]	Real-time (≥ 20 fps target)
Energy per weed (meristem)	~230 J (CO ₂ /diode avg.) to ~1400 J (532 nm) [6]	Platform- and species-dependent
Empirical validation	N/A for this design	Pending prototype field trial (future work)

Limitations and Future Scope

This work is presented at the design stage; the figures in Section 7 are literature-reference values and explicit design targets, not measurements from a deployed prototype. Detection accuracy and kill efficacy for the specific CNN architecture and laser configuration proposed here have not been empirically measured, and will depend on crop type, weed species mix, canopy density, and field lighting conditions, none of which are controlled for in the literature figures cited. The dose-control strategy currently covers the species and stem-diameter ranges reported in the cited dose-response studies [5], [6]; extending it to additional weed species will require further calibration. Eye and skin safety around the laser module, and regulatory compliance for outdoor high-power laser operation, are treated only at the design-interlock level in Section 6.3 and require a full safety assessment before field deployment. Future work includes building and field-testing a prototype against the targets in Table II, extending the



dose controller to a wider range of weed species, and evaluating a fiber-laser configuration for higher-throughput row coverage.

VIII. CONCLUSION

This paper has presented the design of an autonomous, CNN-guided laser weeding system that combines real-time crop-weed detection, 3D meristem localization, species-aware laser dosing, and closed-loop treatment verification.

By grounding its evaluation plan in six recent laser-weeding studies rather than presenting targets in isolation, the design is positioned to be benchmarked directly once a working prototype is built. Laser-based weed control offers a chemical-free, soil-preserving alternative to herbicides and mechanical weeding, and the pipeline proposed here is intended to narrow the gap the literature identifies between high model-level detection accuracy and lower end-to-end field kill efficacy.

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