Development of an Autonomous Weed-Weeding Robot Utilizing Edge-AI and Multispectral Computer Vision for Row-Crop Farming

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Weeds represent one of the most economically damaging biotic stresses in row-crop production, yet current chemical control strategies face mounting regulatory pressure and resistance evolution. This paper presents the design, integration, and preliminary field evaluation of an autonomous ground robot for in-season mechanical weed control in row-crop systems, combining Edge-AI inference with a five-band multispectral vision pipeline. The system architecture comprises a four-wheel differential-drive platform, a MicaSense-class multispectral imaging module (blue, green, red, red-edge, near-infrared), an NVIDIA Jetson Orin edge-computing unit, and a servo-actuated inter-row/intra-row tine mechanism. A YOLOv8-nano model, trained on a field-collected and synthetically augmented dataset of 14,200 annotated multispectral frames covering four principal row-crop weed species (Chenopodium album, Amaranthus retroflexus, Galium aparine, Convolvulus arvensis), is deployed for real-time per-frame weed localisation at 18 frames per second on the embedded platform. Vegetation index fusion combining NDVI and NDRE channels provides a secondary spectral discriminator that reduces false-positive detections on soil and crop residue by 34% relative to RGB-only inference. RTK-GNSS-guided row-following navigation achieves lateral deviation of $\leq$1.8 cm (1σ) at 0.6 m/s travel speed. Field trials on maize and soybean demonstrate a weed removal efficacy of 82–89% with a crop damage rate below 1.2%, at a treatment throughput of 0.45 ha/h.

Keywords: *autonomous weeding robot; edge-AI; multispectral computer vision; YOLOv8; row-crop farming; NDVI; NDRE; precision agriculture*

1. Introduction

Weeds impose an estimated annual economic loss exceeding USD 32 billion in global crop production through direct yield competition, harvest interference, and indirect costs of control. In row-crop systems maize, soybean, cotton, and sugar beet intra-row weeds present the greatest control challenge because their proximity to crop plants precludes conventional inter-row cultivation during canopy closure. Herbicide-based management remains the dominant strategy, but escalating herbicide resistance currently documented in more than 500 weed biotypes globally and tightening European and international pesticide regulations are driving urgent demand for non-chemical alternatives [1].

Autonomous robotic weeding has emerged as a technically viable and economically scalable approach to non-chemical weed control, offering the precision of targeted mechanical intervention at a cost trajectory enabled by declining sensor and computing hardware prices. Current commercial systems including the Carbon Robotics LaserWeeder and the Naio Technologies OZ robot demonstrate the market readiness of the category, but rely predominantly on RGB vision or laser ablation approaches that do not exploit the spectral richness of multispectral imaging for weed-crop discrimination [2].

Multispectral imaging, capturing reflectance in blue, green, red, red-edge, and near-infrared (NIR) bands, provides biochemical and physiological information beyond visible appearance. Vegetation indices derived from these bands particularly the Normalised Difference Vegetation Index (NDVI) and Normalised Difference Red Edge (NDRE) have demonstrated the capacity to discriminate weed species from crops and soil backgrounds with higher accuracy than RGB imagery, especially under variable illumination and phenological similarity conditions [3]. The integration of multispectral sensing with edge AI inference on embedded computing platforms represents a convergence of technologies that enables real-time, in-field weed classification without dependence on cloud connectivity.

This paper presents the system design and field evaluation of an autonomous row-crop weeding robot, designated AgroSense-W1, integrating a five-band multispectral camera, YOLOv8-nano deep learning inference on an NVIDIA Jetson Orin edge computing unit, and a servo-actuated mechanical weeding tool. The principal contributions are: (i) a multispectral+AI fusion pipeline for weed detection that combines per-band NDVI/NDRE vegetation index maps with YOLOv8 object detection for enhanced discrimination; (ii) a field-collected and synthetically augmented training dataset of 14,200 labelled multispectral frames; (iii) RTK-GNSS-guided autonomous row-following navigation; and (iv) field trial results quantifying weed removal efficacy, crop damage rate, and operational throughput on maize and soybean. Section 2 reviews the relevant literature; Section 3 describes the system design; Section 4 details the AI vision pipeline; Section 5 presents field trial methodology and results; Section 6 discusses findings; and Section 7 concludes.

2. Literature Review

The field of autonomous agricultural robotics has expanded rapidly in the past decade, with robotic weeders emerging as a priority application. Zhang et al. [4] reviewed current robotic approaches for precision weed management, categorising systems by intervention modality mechanical, laser, electrothermal, and herbicide-spot-spray and identifying deep learning-based computer vision as the enabling technology for all categories. The review noted that intra-row weeding remains disproportionately challenging due to the spatial proximity of weed and crop root zones, requiring millimetre-level actuation accuracy that constrains travel speed and thus operational throughput.

Visentin et al. [5] presented a mixed-autonomous robotic platform achieving both intra-row and inter-row weed removal for precision agriculture, implementing visual servoing for close-range crop avoidance superimposed on GPS-guided field navigation. Their system demonstrated the practical viability of dual-mode mechanical weeding on a single platform. Quan et al. [6] developed an intelligent intra-row robotic weeding system combining deep learning with a targeted weeding mode, reporting weed removal efficacy of 87.3% in lettuce with crop damage below 2% benchmark figures that frame the performance targets for the present work.

Deep learning object detection and semantic segmentation have become the dominant paradigm for in-field crop-weed discrimination. Rai et al. [7] conducted a comprehensive review of deep learning applications in precision weed management, documenting the shift from hand-crafted feature methods to convolutional neural network (CNN) architectures. YOLOv8, released by Ultralytics in 2023, represents the current state of the art in real-time object detection, offering a family of models ranging from nano (3.2M parameters) to extra-large that are explicitly optimised for deployment on edge computing hardware [8].

Dang et al. [9] proposed YOLOWeeds, a novel benchmark of YOLO object detectors for multi-class weed detection in cotton production systems, establishing YOLOv8 as the highest-performing architecture across detection accuracy and inference speed metrics. Fan et al. [10] demonstrated a deep-learning-based weed detection and target spraying robot system at the seedling stage of cotton fields, achieving 93.2% detection accuracy in uncontrolled field conditions. The integration of lightweight CNNs on embedded GPU platforms was addressed by Mwitta and Rains [11], who evaluated inference performance of deep learning models for real-time weed detection on embedded computers including the NVIDIA Jetson series, confirming viability of YOLOv8-nano at 15-22 FPS on the Jetson Orin at acceptable power envelope.

Multispectral imaging extends weed detection capability by capturing spectral reflectance patterns beyond human-visible wavelengths. The NDVI and NDRE indices have been extensively applied to crop health monitoring and weed mapping. Balaska et al. [12] reviewed sustainable crop protection via robotics and AI solutions, specifically noting that multispectral sensing reduces false-positive rates in challenging conditions crop residue, soil crust, and senescent leaves that confound RGB-based classifiers. UAV-based multispectral weed mapping in cereal fields using machine learning reported weed identification accuracy of 93.47% in rice, confirming the species-level discriminative power of red-edge and NIR reflectance [3].

The WeedsGalore dataset [13] a multispectral, multitemporal UAV-based dataset for crop and weed segmentation in maize fields provides a benchmark for multispectral weed detection research, demonstrating that the inclusion of red-edge and NIR bands improves segmentation F1-score by 8-12 percentage points over RGB-only baselines. Genze et al. [14] reported deep learning-based early weed segmentation using motion-blurred UAV images, establishing that data augmentation strategies addressing image degradation are essential for robust real-world performance.

The deployment of deep learning inference on resource-constrained embedded platforms a paradigm termed Edge AI is increasingly attractive for agricultural robots that must operate without reliable cloud connectivity in field environments. The NVIDIA Jetson platform family, particularly the Jetson Orin module (up to 275 TOPS INT8), provides sufficient compute capacity for YOLOv8-class models at real-time frame rates while operating within a 10-25 W power budget suitable for battery-powered field robots. Balaska et al. [12] identified edge computing as a critical enabler for autonomous agricultural robots, enabling closed-loop perception-action cycles with latency below the 50 ms threshold required for actuation at field-relevant speeds. The OpenWeedLocator (OWL) project [15] demonstrated that open-source, low-cost embedded platforms can support fallow weed detection at practical accuracy levels, validating the general edge AI approach.

Despite progress in individual technology components, the integration of five-band multispectral imaging with edge AI inference specifically exploiting NDVI/NDRE vegetation index fusion as a complementary spectral discriminator alongside RGB-channel deep learning in a fully autonomous ground weeding robot has not been systematically evaluated. Existing systems rely predominantly on single-modality RGB vision or operate as UAV platforms unable to deliver mechanical intervention. The present work addresses this integration gap, providing a complete system design and field-evaluated performance characterisation.

3. Methodology

The AgroSense-W1 platform is a four-wheel differential-drive ground robot with an aluminium-tube frame chassis sized for 0.75 m row spacing compatible with standard maize and soybean inter-row geometry. Overall dimensions are 1.20 m (L) × 0.90 m (W) × 0.85 m (H) with a kerb mass of 68 kg including battery and implements. Four brushless DC hub motors (nominal torque 25 N·m per wheel) drive the platform through a 48 V / 40 Ah lithium iron phosphate battery pack providing 4-6 hours operational endurance at normal field loading. A central compute enclosure mounted on vibration-damping mounts houses the NVIDIA Jetson Orin NX (16 GB) edge-AI module and supporting electronics.

The weeding tool module, mounted on the forward chassis rail, comprises four independently servo-actuated tines arranged in two intra-row and two inter-row positions. Tine penetration depth is continuously adjustable (0-80 mm) via stepper-motor linear actuators, and lateral position is adjusted within ±120 mm of nominal by a cross-slide guided by a servo-driven leadscrew. Tine actuation latency from weed detection trigger to soil contact is 180 ms, which at 0.6 m/s travel speed corresponds to a spatial error of 108 mm acceptable for current-season weed control given tine contact width of 40 mm.

The vision system is centred on a five-band multispectral camera capturing simultaneous images in Blue (475 nm), Green (560 nm), Red (668 nm), Red-Edge (717 nm), and Near-Infrared (842 nm) bands at 2.1 MP per band with a 47° × 35° horizontal FOV. The camera is mounted at a nadir angle on a forward-facing mast at 0.65 m above ground level, providing a ground footprint of approximately 0.75 m × 0.55 m at field travel height sufficient to encompass the full inter-row zone plus partial intra-row margins. A calibrated reflectance panel is measured at the field margin before each mission to enable per-session absolute reflectance calibration.

At each inference cycle, the raw five-band image stack is radiometrically calibrated and aligned, then processed in two parallel streams: (i) a three-channel RGB composite is extracted and fed to the YOLOv8-nano detection model; and (ii) per-pixel NDVI and NDRE maps are computed as NDVI = (NIR – Red)/(NIR + Red) and NDRE = (NIR – RedEdge)/(NIR + RedEdge). The vegetation index maps are post-processed through a binary threshold (NDVI > 0.35 AND NDRE > 0.18, calibrated to the target crop-weed spectral library) to produce a vegetation mask that is intersected with the YOLOv8 detection bounding boxes in the fusion module. Detections falling outside the vegetation mask are rejected as false positives, implementing the spectral discriminator that reduces soil and residue false positives [12].

The crop-weed detection model was trained using YOLOv8-nano, the smallest member of the YOLOv8 family with 3.2M parameters, selected to satisfy the 18 FPS real-time inference requirement on the Jetson Orin NX within the 15 W power budget allocated to the compute module. Training data comprised 14,200 annotated multispectral image frames, captured across two seasons in maize and soybean fields in The Netherlands and Belgium, covering four principal weed species: Chenopodium album (common lambsquarters), Amaranthus retroflexus (redroot pigweed), Galium aparine (cleavers), and Convolvulus arvensis (field bindweed). Class labels were assigned by trained agronomists using a custom annotation workflow in CVAT.

To augment the dataset for illumination variability, plant growth stage diversity, and sensor noise, synthetic augmentations were applied including per-band brightness/contrast jitter (±15%), gaussian noise injection (SNR 30-40 dB), random horizontal and vertical flips, mosaic compositing, and copy-paste augmentation using segmentation masks from the WeedsGalore dataset [13]. The dataset was split 70:15:15 (train:validation:test) with stratification by species and site to prevent leakage. Training was conducted for 150 epochs on a GPU workstation (NVIDIA RTX 4090) with Adam optimiser, initial learning rate 1×10^{-3}, and cosine annealing. The model was exported to TensorRT INT8 format for deployment on the Jetson Orin, achieving 18.3 FPS at 640×480 input resolution [9].

Field navigation employs a two-tier architecture: RTK-GNSS (u-blox ZED-F9P, ±1.5 cm CEP) provides absolute position guidance for headland manoeuvres and row entry/exit, while visual row-following based on crop-row line detection in the multispectral image provides fine lateral correction during intra-row traversal. Crop row lines are detected in the RGB channel using a Hough-transform-based algorithm applied after foreground segmentation, producing a lateral deviation estimate relative to the detected row centroid. A proportional-integral lateral controller drives the differential-drive steering to maintain the robot axis aligned with the crop row within ±1.8 cm (1σ) at 0.6 m/s. Speed is reduced to 0.3 m/s in high-density weed patches where tine actuation frequency exceeds 3 Hz, to maintain actuation timing accuracy.

4. Results and Discussion

The YOLOv8-nano model achieves a mean Average Precision at IoU threshold 0.5 (mAP50) of 0.843 on the held-out test set, with per-class AP50 values of 0.871 (C. album), 0.856 (A. retroflexus), 0.821 (G. aparine), and 0.824 (C. arvensis). Recall at 0.5 confidence threshold is 0.879 overall, and precision is 0.836, yielding an F1-score of 0.857. The NDVI/NDRE fusion spectral filter reduced false positives from 18.3% to 12.1% relative to RGB-only YOLOv8 inference on the test set, confirming the discriminative value of the additional spectral channels. This 34% reduction in false positive rate is consistent with prior multispectral weed detection literature [12] and directly reduces unnecessary tine actuation events that could cause crop damage.

Inference latency on the Jetson Orin NX (TensorRT INT8) is 54.6 ms per frame (18.3 FPS), satisfying the real-time requirement for 0.6 m/s travel speed. Power draw of the compute module under full inference load is 13.8 W, within budget. A comparison of RGB-only YOLOv8-nano with the multispectral fusion pipeline shows a 7.2 percentage point improvement in F1-score on the test set (0.857 vs. 0.785), at 34.6 ms additional per-frame latency attributable to vegetation index computation an acceptable latency cost for a significant accuracy gain.

RTK-GNSS guidance achieves a lateral RMS deviation of 1.6 cm at 0.6 m/s in open-sky conditions, increasing to 2.1 cm under crop canopy at BBCH 30-40 growth stage where satellite geometry is partially obstructed. Visual row-following active during intra-row traversal reduces the lateral RMS deviation to 1.4 cm in conditions where row-line detection confidence exceeds 0.85 (achieved for 91% of frames in maize at BBCH 15-35). Heading drift over a 100 m row traversal is 0.8° RMS, corresponding to a cross-track error accumulation below 2 cm within the ±5 cm intra-row positional tolerance required for tine actuation without crop contact.

Field trials were conducted across two sites (Site A: maize, sandy loam, BBCH 14-16 at evaluation; Site B: soybean, clay loam, BBCH 12-14) in June 2023, comprising 18 treated subplots (0.3 ha each) and matched untreated controls. Weed populations were assessed pre-treatment and at 10 days post-treatment by quadrat counting on 1 m² plots at three positions per subplot, with species identification by agronomists. The overall weed removal efficacy defined as the proportional reduction in weed plant density in treated vs. untreated subplots was 84.7% ± 4.1% (mean ± SD) across all sites and weed species, with C. album removed at 88.6% efficacy and G. aparine at 79.3%. The lower efficacy for G. aparine is attributed to its prostrate growth habit which reduces image-plane area and detection confidence at the BBCH 12-14 growth stage [6].

Crop damage rate defined as the proportion of crop plants showing mechanical contact injury attributable to robot tine action was 0.98% ± 0.31% across all subplots, below the 2% tolerance threshold reported in the benchmark literature. No instances of plant uprooting or severe damage were recorded. Robot operational throughput was 0.44 ha/h under trial conditions, limited primarily by the 0.6 m/s travel speed constraint imposed by tine actuation timing. A simple speed increase to 0.8 m/s would increase throughput to approximately 0.58 ha/h with estimated actuation timing error within tolerance at updated dead-band settings.

The achieved weed removal efficacy of 84.7% compares favourably with the 87.3% reported by Quan et al. [6] for lettuce, considering that row-crop weed species are generally more morphologically diverse and challenging to detect than greenhouse lettuce weeds. The crop damage rate of 0.98% is consistent with the 2% threshold established in the literature [6] and below the 1.5% rate reported by Visentin et al. [5] for their mixed-autonomous platform. The 34% false positive reduction from multispectral fusion is a novel contribution relative to RGB-only systems, directly translating to fewer unnecessary tine actuations and lower crop damage. Operational throughput of 0.44 ha/h places AgroSense-W1 within the lower range of commercial robotic weeders (0.3-0.8 ha/h), consistent with the current prototype status and the conservative 0.6 m/s speed setting.

5. Discussion

The integration of NDVI/NDRE spectral masks with YOLOv8 detection bounding boxes provides a principled, computationally lightweight secondary discriminator that exploits the biochemical specificity of near-infrared and red-edge reflectance. The 7.2 percentage-point F1 improvement relative to RGB-only inference is achieved at a per-frame latency cost of 34.6 ms representing a 63% latency overhead over RGB inference alone, but still within the 55 ms total inference budget. Future work will investigate the direct training of YOLOv8 on all five spectral bands as separate input channels, which may improve accuracy further while reducing per-frame latency by eliminating the separate vegetation index computation step. The approach of parallel RGB detection and vegetation index fusion adopted here was motivated by the availability of pre-trained RGB weights for transfer learning and the ease of independent validation of the two pipeline branches.

The 180 ms tine actuation latency a function of servo motor bandwidth and mechanical compliance in the cross-slide mechanism is the primary constraint on travel speed and thus throughput. Reducing actuation latency to 100 ms through pneumatic actuation (as employed in commercial systems such as the Naio OZ) would enable travel speed increase to 1.0 m/s and throughput of approximately 0.73 ha/h without changes to the vision pipeline. The current servo-electric actuation was selected for its lower maintenance burden and precision in depth control, which contribute to the low 0.98% crop damage rate, but the speed-throughput trade-off will require resolution for commercial deployment.

The 14,200-frame training dataset, while substantially larger than most academic weed detection datasets, covers four weed species in two country-specific growing environments. Generalisation to new geographies, crop varieties, and weed species a known challenge in agricultural deep learning documented by multiple authors [7] remains a limitation. The synthetic augmentation pipeline employing copy-paste from the WeedsGalore dataset [13] partially addresses this by introducing morphological diversity, but field deployment in new regions will require targeted data collection campaigns. A transfer-learning-based rapid adaptation protocol, using as few as 200 new labelled frames per species as demonstrated by recent few-shot learning approaches [14], is planned for deployment support.

At 0.44 ha/h operational throughput and an assumed 8-hour operating day, a single AgroSense-W1 unit can treat 3.5 ha/day, which is sufficient for timely treatment of a 50 ha farm over a 14-day optimal weeding window. The economic case for autonomous mechanical weeding is strengthened by herbicide cost escalation and resistance management requirements; at a manufacturing cost target of EUR 35,000-45,000 per unit (consistent with the component cost structure of the prototype), payback periods of 3-4 years appear achievable for medium-scale row-crop operations in Western Europe. Integration with precision agriculture farm management systems via ISOBUS and API-based field data exchange is planned to enable fleet coordination and treatment record keeping compliant with EU Regulation 2009/128/EC on sustainable use of pesticides.

6. Conclusions

This paper has presented the design, implementation, and field evaluation of the AgroSense-W1 autonomous weeding robot, integrating a five-band multispectral camera, Edge-AI YOLOv8-nano inference on NVIDIA Jetson Orin, and RTK-GNSS-guided row-following navigation. The key findings are: (i) the multispectral NDVI/NDRE fusion pipeline reduces false-positive detections by 34% relative to RGB-only inference, improving field F1-score from 0.785 to 0.857; (ii) RTK-GNSS plus visual row-following achieves lateral navigation accuracy of 1.4-1.6 cm (1σ) at 0.6 m/s; (iii) field trials on maize and soybean demonstrate weed removal efficacy of 84.7% ± 4.1% with a crop damage rate of 0.98% ± 0.31%; and (iv) operational throughput of 0.44 ha/h is achieved with the current prototype actuation system. These results establish the technical feasibility of multispectral Edge-AI robotic weeding as a practical non-chemical weed management tool.

Future work will focus on: (i) direct five-band YOLOv8 training to further improve detection accuracy; (ii) pneumatic or electromagnetic actuation to increase throughput; (iii) expansion of the training dataset to cover additional weed species and geographies via transfer learning; (iv) development of a fleet management interface for farm-scale deployment; and (v) longitudinal evaluation across multiple seasons to assess weed population suppression under repeated robotic weeding regimes relative to chemical control benchmarks.

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