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Multi-YOLO Comparative Deep Learning-integrated Robotic System for Precision Weed Control in Rice (*Oryza sativa* L.)

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ABSTRACT

Background: Traditional weed management in rice farming relies heavily on herbicides and labor-intensive manual practices, which are often costly, inefficient and environmentally unsustainable. The lack of precision in conventional approaches results in excessive chemical use, crop damage and inconsistent weed control. To address these challenges, intelligent robotic systems integrated with artificial intelligence offer a promising pathway toward sustainable and precise weed management.

Methods: This study presents a comprehensive analysis of a modular autonomous robotic platform that integrates advanced mechatronic design with AI-driven visual intelligence for rice-field weed management. Three deep learning models, YOLO v5, v7 and v8, were trained on rice weed image datasets for real-time weed detection and classification. Advanced image-processing algorithms were employed for crop-weed discrimination and row guidance. The robotic platform, powered by an NVIDIA Jetson Nano and planetary gear motors, features a dual-action mechanical subsystem consisting of a rotary weed cutter for physical removal and a cultivator–incorporator for in-situ biomass mixing. Field experiments were conducted at the Agricultural Farm of Siksha 'O' Anusandhan (SOA) University, Odisha, India.

Result: The robotic platform demonstrated stable real-time navigation, achieving a lateral tracking deviation of approximately ±2 cm under controlled test conditions and less than 5 cm in field environments, as quantified by measuring the robot's offset from the crop-row centreline at fixed reference intervals. Field trials demonstrated approximately 95% weed control efficiency and less than 2% crop damage. Compared with conventional practices, the robotic system reduced herbicide use by nearly 70% while maintaining stable operation under representative paddy-field conditions. Detection accuracy and field-level weed-removal efficiency are distinct evaluation metrics. The proposed AI-integrated robotic platform demonstrates strong potential for precision weed management in rice cultivation. By combining deep-learning-based vision with a robust mechatronic framework, the system significantly reduces chemical dependency, improves weed-control accuracy and enhances environmental sustainability. This work highlights a viable pathway to scalable, eco-friendly automation in paddy-field agriculture.

Key words: Autonomous weeding robot, NVIDIA jetson nano, Precision agriculture, Real-time navigation, Rice (*Oryza sativa* L.), Sustainable weed management, v7, v8 Object detection, YOLOv5.

INTRODUCTION

Modern farming systems face significant challenges due to an excessive reliance on chemical herbicides, which have led to biodiversity loss, soil degradation, the emergence of herbicide-resistant weed species and increased production costs (Rao *et al.*, 2020; Nath *et al.*, 2024). The European Union and other regions have set high standards to convert 30-40% of farmland to organic production by 2030 (Pânzaru *et al.,* 2023), as a result of global laws aimed at promoting sustainable practices. Rice farming, in particular, requires innovative weed management approaches, since it is one of the most herbicide-intensive crops (Arockia Doss *et al.*, 2023; Kokilam *et al.*, 2023; Bandyopadhyay *et al.*, 2024). Recent research, including our previous work, explored autonomous robotic weeders as potential alternatives to chemical control. Earlier studies primarily focused on machine vision for weed detection and eradication methods (Mohanty *et al.*, 2025). This research focuses on developing a robotic platform with artificial intelligence (AI) algorithms specifically designed for precision weeding in paddy and other crops grown in paddy-based cropping systems.

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System architecture and operational framework

The robotic platform was designed primarily for mechanical weed suppression in high-density organic

farming systems, where weed-to-crop ratios can exceed 12:1, posing a significant challenge for herbicide-free agriculture. (Mesías-Ruiz *et al.*, 2024).

To address this demand, new computational frameworks were created, including a topology-aware row detection algorithm and a multispectral plant discrimination model that were tuned for the platform's AI-powered perception stack, which combines convolutional neural networks (CNNs) for spatial pattern recognition with adaptive decision-making algorithms that adjust weeding intensity in real time depending on Phyto-morphological inputs (Zhu *et al.*, 2025). This split-processing architecture separates structural row navigation from weed species detection, enabling both tasks to run concurrently (Gao *et al.,* 2025). This parallelism improves real-time response and precision in targeted weed suppression.

The AI-driven perception stack has a split architecture (Ozer *et al.*, 2025), as shown in Fig 1. CNN-based spatial pattern recognition examines crop row topology for navigation (left stream), while a separate multispectral analytic pipeline classifies weed species (right stream) (Vignesh *et al.*, 2025). Both outputs are fed into a central decision-making unit that regulates actuator intensity and path correction in real time.

Integrated methodological framework and software architecture

The methodological approach for autonomous weed management is designed to address the inherent challenges of rice cultivation, namely its row-based structure, which creates two distinct weeding spatial regimes: inter-row clearance (removing weeds between crop rows) and the more complex intra-row eradication (identifying and eliminating weeds within the crop line, requiring precise plant-level discrimination) (Qu *et al.*, (2024). To navigate this environment, the robotic platform utilises a modular propulsion system comprising an active front-wheel drive, powered by a single cage-wheel motor and stabilising rear casters. The system's operational intelligence is governed by a sophisticated software architecture running on an NVIDIA Jetson Nano embedded computer, which synchronises the vision, navigation and actuation subsystems for continuous, real-time performance. The software workflow can be broken down into three core functions: perception and localisation, decision and control and actuation.

Technical implementation

In the software architecture shown in Fig 2, detection data from the YOLO model is routed through an intermediary buffer task to facilitate asynchronous communication between the application and control layers. This design ensures that time-sensitive control processes, such as navigation and weeding, operate on perception data without being delayed by ongoing inference computations, maintaining the control layer's responsiveness (Lan *et al.*, 2024). The system is organised into a two-layer design to enhance modularity and maintainability. This structure, supported by asynchronous communication protocols and the NVIDIA Jetson Nano's processing capabilities, enables non-blocking data flow through the buffer (Dang *et al.*, 2025). This ensures that updates to perception algorithms or the web-based dashboard for remote monitoring do not impact the core control logic, enabling robust, vision-guided autonomous operation in resource-constrained environments (Moghadam *et al.*, 2026).

Fig 3 compares the YOLO backbone architectures of v5, v7 and v8. The backbone of YOLOv5 has undergone significant changes compared to previous versions of the model. It mainly utilises the Focus structure for down-sampling, as well as the C3 (Cross Stage Partial) module, a modified version of the CSP constraint designed for enhanced gradient flow. The backbone also includes an SPP (Spatial Pyramid Pooling) layer to expand the receptive field.

YOLOv7 has a more complex backbone that incorporates the E-ELAN (Extended Efficient Layer Aggregation Network) computing block. This structure is designed to improve the network's learning capabilities while preserving the original gradient route. It also uses SPP-CPC (Spatial Pyramid Pooling with Cross-stage Partial

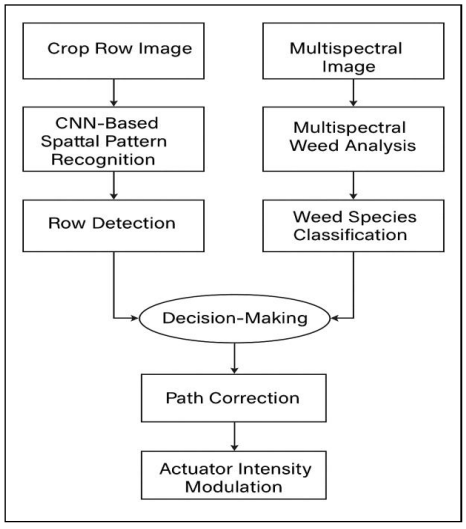


Fig 1: System architecture flow diagram.

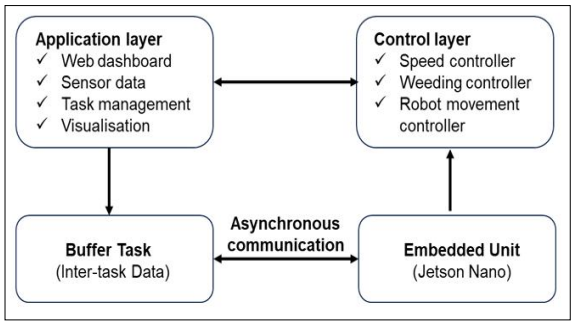


Fig 2: Perception and control architecture for high-density paddy fields.

Connections) for feature integration. The backbone of YOLOv8 replaces the C3 module with the C2f (Cross Stage Partial with 2 Convolutions) module, which provides improved gradient flow. It also employs an SPPF (Spatial Pyramid Pooling Fast) module, a faster version of SPP and transitions to an anchor-free detection head, simplifying the architecture.

Mechanical architecture framework and technical specifications of the robot

The robot system is designed to minimise soil compaction and maximise traction under saturated paddy field conditions. Fig 4 shows the mechanical flow diagram, which integrates several subsystems, including the chassis, drive system, vision system and cultivating tool assembly. The wheel assemblies with cage wheels are attached to the chassis *via* a chain-sprocket transmission mechanism and a motor-mounted shaft. This ensures effective torque transfer and improved grip on wet soil conditions. A Jetson Nano processing unit running the YOLO object detection model is connected to cameras as part of the vision system, enabling the real-time identification of crops and weeds (Zhang *et al.*, 2026; Ramos-Sanchez *et al.*, 2026).

A knuckle joint (made of Grade 30C8 steel) connects the motor mounting body to the main robot chassis, as shown in Fig 5. For autonomous operation, actuation is provided by a NEMA 17 stepper motor, which is coupled to the steering system and governed by a Jetson Nano embedded controller. To ensure algorithmic stability and power efficiency during row-following, the software imposes a ±10° operational range around the neutral position. This soft limit prevents oversteer and mechanical shock while providing sufficient articulation for accurate path correction (Raj *et al.*, 2018).

Cage-wheel propulsion system

The robot utilises a front-driven cage-wheel propulsion system (Fig 6), designed for navigating soft, muddy terrain. A single, independently powered front cage wheel provides driven traction, while passive rear stabilisers ensure balance. The open-frame wheel design enhances grip on waterlogged soil, minimises debris accumulation and reduces slippage, which is critical for precise inter-row navigation and weeding tasks.

Motor mounting configuration with chain and sprocket assembly

The propulsion is powered by one high-torque 12V DC worm gear motor, each delivering a rated torque of 70 kg·cm (110 kg·cm stall torque) at approximately 10 RPM. The motor is mounted on the front chassis for optimal weight distribution and is connected to the drive shaft *via* a slip-free torque transmission, as shown in Fig 7(a). The worm gear design provides inherent braking and high torque at low speeds, making it an ideal choice for agricultural applications. The mounting frame is built to withstand field

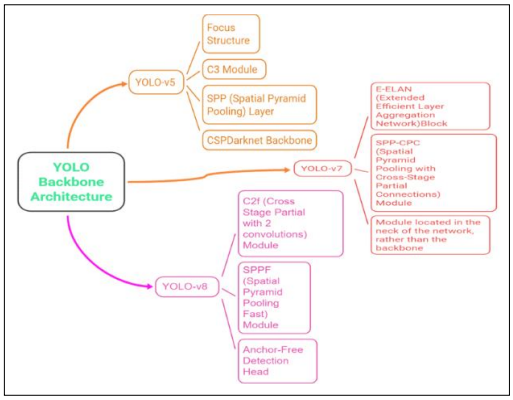


Fig 3: YOLO backbone evaluation and modules of YOLOv5, v7 and v8.

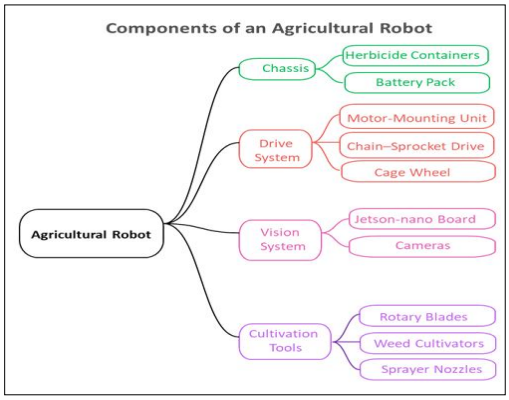


Fig 4: Flow diagram of mechanical chassis and driving system, vision system and cultivation tools components.



Fig 5: Motor-to-chassis mounting arrangement.

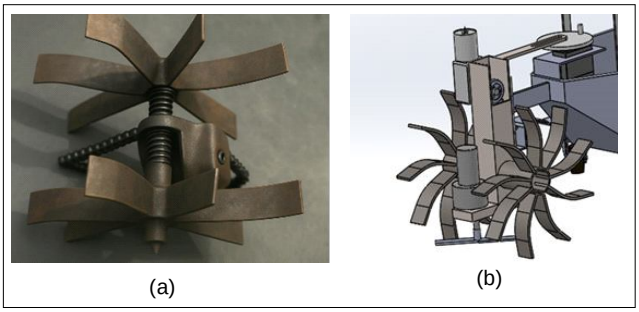


Fig 6: Top view of cage wheel assembly (a) photographic, (b) CAD.

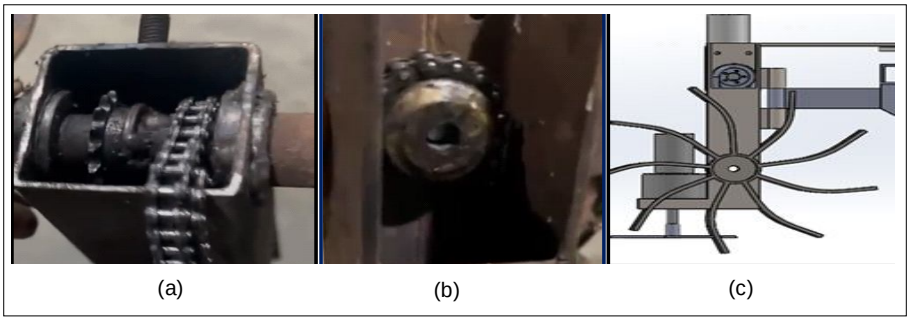


Fig 7: Chain-sprocket drive assembly: (a) Photographic view, (b) Side view of drive arrangement and (c) CAD side view.

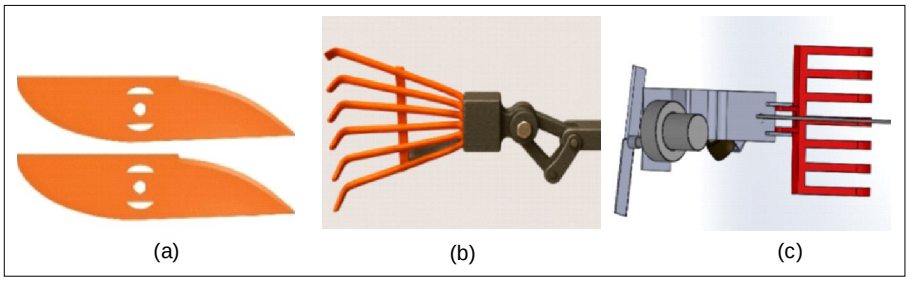


Fig 8: (a) Rotary blade, (b) Cultivator, (c) CAD model view of rotary blade and cultivator.

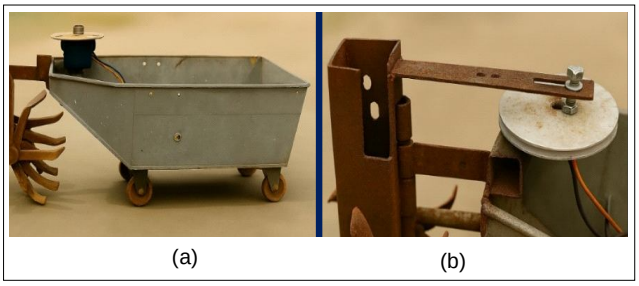


Fig 9: (a) Chassis, (b) Steering module of the robot.

vibrations and impacts, ensuring longevity. The motor is bolted to the wheel mount via four mounting bolts. The motor shaft is fitted with the driven sprocket, which engages with the driver sprocket through a drive chain to transmit power. A precision sprocket is securely affixed to a 16 mm inner diameter drive shaft Fig 7(b) using a set screw, ensuring reliable torque transmission. The gearbox is pre-lubricated with high-performance grease to reduce friction and ensure durable, low-maintenance operation under variable field loads. A roller chain and sprocket arrangement Fig 7(c) transmit power from the motor's output shaft to the wheel axle. The system is designed to minimise backlash and slippage, with an adjustable chain tensioner that maintains wheel synchronisation and compensates for elongation over time. This ensures consistent and stable power delivery across uneven or hilly terrain.

Rotary blade as a weed cutter and the cultivator

A horizontally rotating blade assembly, as shown in Fig 8, positioned at an optimal height below the chassis, severs weeds between crop rows.

This mechanical subsystem features a dual-action mechanism that integrates a rotary weed cutter with a cultivator-incorporator.

Chassis with steering design

The chassis, as shown in Fig 9(a), is constructed from high-strength, lightweight materials (aluminium alloy) and designed to support all subsystems while withstanding field vibrations and environmental challenges. The steering module of the robot Fig 9(b) utilises simple, low-cost and no complex linkages. Self-aligning Casters automatically follow the path of motion with a maximum turn angle of 10°, driven by a NEMA 17 stepper motor. Fail-safe electromagnetic brakes are integrated to deploy automatically in the event of power failure, ensuring the robot's position is secured. The steering system, controlled by the Jetson Nano board, is software-limited to an operational range of ±10° from neutral, preventing oversteer while ensuring precise path correction. The steering wheel is attached to a stepper motor, which is in turn mounted on the chassis.

Protection and safety systems

The chassis is elevated to provide sufficient ground clearance, protecting critical drive and electronic components from uneven terrain, crop residue and debris. Simultaneously, the cutting blades are positioned below the chassis to engage weeds at or below the soil surface. This purposeful vertical offset ensures effective weeding accuracy and crop safety while maintaining overall mobility and operational reliability in challenging field conditions. This spatial design, combined with synchronisation that reduces the machine vision processing lag to less than

200 ms, reduces the positional error between plant identification and mechanical action to less than 2 cm, resulting in accurate intervention. Power is supplied by modular Lithium-ion battery packs rated at 12 V and 12 Ah. Routine maintenance, including chain tension adjustment, wheel alignment verification and motor mounting inspection, is performed to ensure system reliability and optimal performance.

Use of appropriate herbicides through pneumatic control

The herbicide delivery system is shown in Fig 10. The system features a pneumatically controlled herbicide delivery mechanism that enables precise, targeted chemical treatment based on real-time weed classification. When a weed is identified using vision-based detection (*e.g.*, YOLO v5, v7 and v8 combined with stereo camera input), the appropriate herbicide is selected from several onboard containers, each labelled with a specific herbicide type. This modular design enables simple refilling, replacement and scaling, depending on the crop type and field size. It ensures that agrochemicals are deployed safely and automatically, aligning with precision agricultural goals.

Mechatronics architecture

The platform's mechatronic architecture is built around a series of 12 V DC actuators equipped with worm-gear transmissions, enabling high torque and precise placement required for farming operations. These actuators drive a modular end-effector system that accommodates interchangeable tools, such as rotary blades and sliding-mount driven tines, to perform a diverse range of soil-intervention tasks. The vibration sensors are strategically mounted near the tool frame to capture oscillatory signatures generated during tool-soil interaction. Deviations from the nominal frequency response are interpreted as indicators of bearing wear, mechanical imbalance, or variations in soil compaction.

MATERIALS AND METHODS

The experiment was carried out during the *kharif* season of 2024 at the Agricultural Research Station, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha. The site is located at an elevation of 58 meters above mean sea level, at 20°15′N latitude and 85°40′E longitude. The experimental field was a medium land with well-drained soil and a uniformly levelled topography. The region is characterised by hot summers and short, moderately cool winters. The majority of annual rainfall is received from the south-west monsoon, although it is often characterised by erratic, uneven distribution, with a tendency toward delayed onset and early withdrawal. Pre-monsoon showers generally occur in late May.

The soil at the experimental site was classified as lateritic. Composite soil samples were collected from the top 15 cm layer of the field for physico-chemical analysis. The analysis revealed that the soil was low in organic carbon (0.43%), available nitrogen (184.3 kg ha^{-1}) and available potassium (130.2 kg ha^{-1}), while available phosphorus (12.05 kg ha^{-1}) was in the medium range. The gross plot size for conducting the experiment was 100 m^2.

RESULTS AND DISCUSSION

This section describes quantitative, computational and qualitative performance on a multi-species rice field dataset with high visual similarity between rice seedlings and weeds, varied illumination and dense multi-scale weed distributions. Field evaluation of the proposed robotic weeding platform was conducted using three YOLO-based detection architectures (YOLOv5, v7 and v8) integrated on the NVIDIA Jetson Nano embedded system. Fig 11 shows the developed weed identification system, which combines precision kinematic control with adaptive machine vision algorithms to achieve the precise use of herbicides for weeds (broadleaf) in paddy fields generated by the three models during autonomous field operation.

Quantitative detection performance is summarised in Fig 12, where YOLOv8 achieved the highest mean mAP@0.5, along with improved precision and recall compared to the other models. It should be emphasised that detection accuracy represents perception-level capability, whereas field-level weed control efficiency reflects the integrated outcome of vision, navigation and mechanical intervention. The YOLO models were evaluated using standard detection metrics (mAP, precision, recall).

The agronomic effectiveness of the platform was assessed independently by measuring weed suppression during field trials. Across replicated trials (n = 3), YOLOv5

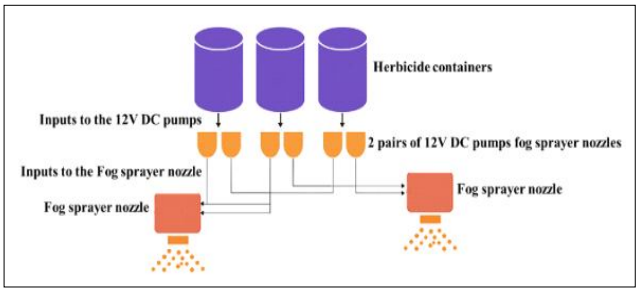


Fig 10: Schematic of the herbicide delivery and spraying system.



Fig 11: The weed identification system using the YOLOv5, 7 and 8 models.

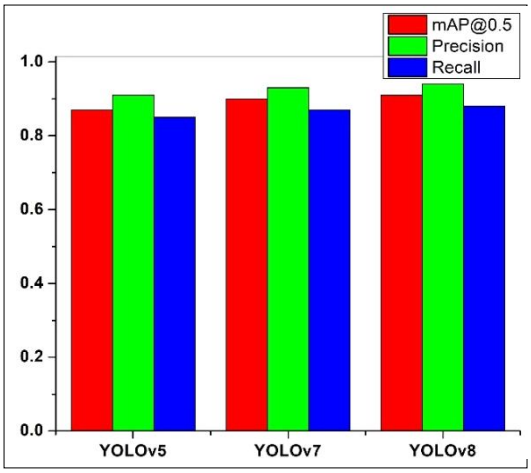


Fig 12: Comparing mAP@0.5, precision and recall for YOLO models.

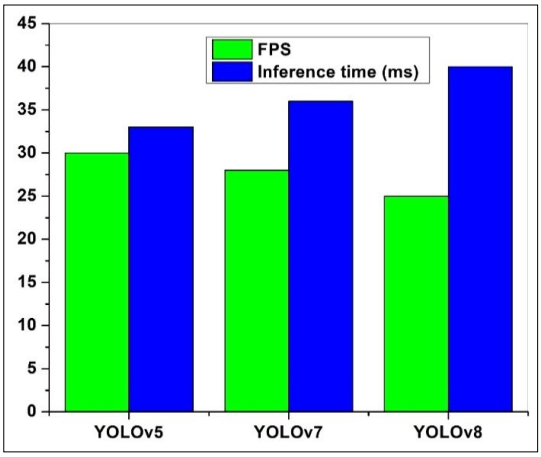


Fig 13: Comparing FPS and inference time for YOLO models.

exhibited weed-suppression efficacy in the range of 88-89%, while YOLOv7 achieved 77-90% and YOLOv8 reached 82-92%, with partially overlapping performance intervals.

Computational benchmarking results are presented in Fig 13, showing that YOLOv5 provided the highest inference throughput, whereas YOLOv8 incurred a modest increase in inference time while remaining within real-time operational constraints. Overall, the robotic system maintained stable navigation performance, with a lateral deviation of approximately ±2 cm in controlled trials and below 5 cm during field operation, based on centreline offset measurements recorded at predefined sampling points along the crop rows, achieving application-level weed control efficacy of approximately 95% with less than 2% crop disturbance.

The comparative evaluation of YOLOv5, v7 and v8 within the proposed robotic weed-management platform highlights the practical trade-offs involved in deploying deep learning for perception in embedded agricultural systems. All three architectures supported real-time crop-weed discrimination under field conditions, with differences reflecting an accuracy-efficiency compromise rather than absolute dominance of a single model. YOLOv5 achieved the highest inference throughput on the Jetson Nano, making it suitable for latency-sensitive navigation tasks, although its detection sensitivity was slightly reduced in dense weed-crop overlap scenarios. YOLOv7 provided intermediate performance but showed greater variability across replicated trials. YOLOv8 attained the highest mean detection accuracy, likely due to improved feature fusion and anchor-free detection, while incurring a modest increase in inference time. Importantly, it remained within the operational real-time constraints of the robotic platform. At the application level, the robotic system demonstrated high weed-control efficacy with minimal crop disturbance, indicating that integrated perception, navigation stability and mechanical actuation can provide an effective alternative to labour-intensive and chemical-dependent weed management practices. A limitation of this study is that the comparative analysis was conducted across three replicated field plots under saturated paddy conditions (n = 3), providing an initial benchmark. Future work will involve larger multi-season trials and adaptive strategies to improve generalisation under diverse agronomic conditions.

CONCLUSION

This work developed and experimentally validated an autonomous robotic system that integrates artificial intelligence for precision weed management in rice cultivation. The proposed platform combines a modular mechatronic design with deep-learning-based vision, implementing three YOLO detection models (v5, v7 and v8) on an embedded NVIDIA Jetson Nano processor. Field trials carried out during the *Kharif* 2024 season across three replicated plots (n = 3) confirmed stable real-time performance, accurate navigation behaviour and effective weed suppression while maintaining low levels of crop disturbance. The comparative evaluation showed that YOLOv8 achieved the strongest mean detection performance, whereas YOLOv5 delivered faster inference speed, illustrating the balance between computational efficiency and perception robustness under practical operating constraints. Overall, the results demonstrate the potential of AI-enabled robotic intervention to reduce reliance on chemical weed control and support more sustainable rice production practices. Future investigations will extend the evaluation to larger, multi-season datasets, improve model adaptability across diverse field conditions and incorporate enhanced sensing and control strategies to enable broader scalability and deployment.

Conflict of interest

On behalf of all authors, corresponding author hereby declares that there are no conflicts of interest-financial, personal, professional, or institutional-that could have influenced the work reported in this manuscript.

All authors confirm that the research was conducted in the absence of any commercial or financial relationships

that could be construed as a potential conflict of interest. No external funding, sponsorship, or support from any organization with a direct interest in the subject matter of the manuscript has influenced the design, execution, interpretation, or reporting of the study.

All authors have approved the final version of the manuscript and agree with its submission to the journal. If any potential conflict of interest arises in the future, the authors will promptly inform the editorial office.

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