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# Smart robotic system guided with YOLOv5 based machine learning framework for efficient herbicide usage in rice (*Oryza sativa* L.) under precision agriculture

Tirthankar Mohanty [a], Priyabrata Pattanaik [a,b], Subhaprada Dash [c], Hara Prasada Tripathy [a], William Holderbaum [b,*]

[a] *Faculty of Engineering and Technology, Siksha 'O' Anusandhan Deemed to be University, Bhubaneswar, Odisha, India*
[b] *Faculty of Science and Engineering, Manchester Metropolitan University, Manchester, UK*
[c] *Faculty of Agricultural Sciences, Siksha 'O' Anusandhan Deemed to be University, Bhubaneswar, Odisha, India*

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ABSTRACT

Conventional weed control methods, reliant on machinery and/or herbicide application, often incurred substantial expenses and yielded imprecise results. An innovative specialised weed control robotic method for accurate and minimal herbicide use is proposed to tackle these issues. Implementing robotic herbicide spraying, weed removal, and incorporation mechanisms along with the image recognition algorithm were introduced, leveraging intelligent automation to reduce costs and environmental hazards. Through image processing, weeds were pointed out and targeted for control in the rice field. A YOLOv5 machine learning framework underwent training using relevant datasets to facilitate precise weed management. The AI-driven robotic system, incorporating advanced image recognition capabilities, exhibited remarkable precision and swiftness, outperforming much better than manual labour in weed removal. This advancement in weed control technology helps farmers to optimise crop productivity, bolster food output, and address the ecological consequences linked with various chemicals; efforts were made to develop a prototype robotic system, which was subsequently built and evaluated in authentic agricultural settings. Experiments were carried out at the Agricultural Farm of SOA University, Binjhagiri, Bhubaneswar, Odisha, India, in a rice field, demonstrating the remarkable accuracy of the robotic system, with a minimal 2% variance from the actual weed quantities. This research highlights the promise of AI-powered weed management solutions in rice cultivation, offering economical and accurate weed detection and elimination functionalities. The robot demonstrates a superior weed control rate of 95%. In addition, the system's performance in incorporating the weeds is at a rate of 90%. It also serves as a blueprint for integrating AI into contemporary agriculture, steering the sector toward a more eco-conscious and economically sustainable future. The AI-driven solution for weed management revolutionises farming practices, equipping farmers with the tools for bountiful yields, increased economic viability, and a commitment to environmental stewardship. This underscores the imperative to prioritise scaling this innovative approach within both industrial and commercial agricultural sectors.

## 1. Introduction

Weeds compete with crop plants for all necessary resources, such as moisture, nutrients, space, and sunlight. They are the alternate host for the disease and pests, reducing crop yields and raising production costs (Gleason et al., 2010). In order to get a good crop yield, weeds must be removed from the cultivated field early in the crop's life cycle (Kubiak et al., 2022). Weed management encompasses various strategies to eliminate and control unwanted plants in the agricultural field. The primary approach involves a coordinated effort to tailor specific weed species or groups (Zimdahl and Basinger, 2024). Farmers can minimise the competition between weeds and their desired crops by employing a comprehensive and coordinated strategy, improving overall yields and efficiency. Weeds are removed using various approaches such as preventive, cultural, physical, mechanical, chemical, biological, and biochemical methods (Shaner and Beckie, 2014). Traditionally, weeds

* Corresponding author.
*E-mail address:* w.holderbaum@mmu.ac.uk (W. Holderbaum).

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are controlled from fields by different tillage practices. Weeds are thoroughly tilled, including their roots, and then removed. Weeds are manually pulled by hand or by using a sharp tool (Wicks et al., 2017). An agricultural weeder is a simple tool that can be operated by hand or attached to a machine like a tiller or power weeder. Hoes, flame weeding, and mulching are all effective weed removal methods. Hoes of various shapes and sizes can be dragged by hand, propelled (as a wheel hoe), or attached to a tractor (Bajwa et al., 2015). But weeding work can be performed more precisely by robots than by humans. Farmers can use robotic weeders to schedule weeding activities based on crop growth stage and weather conditions. Robots can work day and night, allowing for more frequent and rapid interventions. This adaptability can lead to better weed management and potentially increased agricultural yields. Robots can work constantly in various weather conditions and without weariness, improving the overall reliability of the weeding operation (Thakur et al., 2023). This uniformity can be especially useful during critical crop growth stages when prompt weeding is required. Machine learning and computer vision technologies enable robots to identify and target weeds better, decreasing crop damage and boosting overall crop growth. This precision also helps to limit the use of herbicides such as chemicals, resulting in more sustainable farming practices. The implementation of robotic technology has the potential to promote additional agricultural advancements. For instance, robot-collected data (on plant health, weed flora, and overall field conditions) may inform other agricultural decisions, putting more aspects of farm management under one unified, data-driven strategy (Campbell, 2022) . Robotic weeding can benefit the environment by decreasing the demand for chemical pesticides and optimising their usage only when truly necessary. Less chemical pollution and soil disturbance are essential benefits that support sustainable agriculture operations. The use of robots to replace manual labour, such as hand weeding crews, can drastically cut labour expenses on weed control (Edan et al., 2009). Though the initial investment in robotic technology may be extensive, the long-term benefits can be significant due to reduced reliance on manual labour and associated expenditures like pay and training (Danaher, 2021). Integrating robotic technologies into agriculture, such as automated weeders, may reduce costs and improve efficiency. Additionally, it enhances the reliability and sustainability of farming methods (Upadhyay et al., 2024). This transition is consistent with economic and environmental aims, resulting in a more sustainable agriculture system. An innovative technique for transforming precision farming practices by incorporating modern robots and artificial intelligence (AI) to reduce pesticide consumption in rice cultivation. Conventional agricultural methods frequently include inappropriate pesticide spraying, resulting in environmental degradation and crop damage (Sharma et al., 2021). The proposed approach involves developing and implementing a robotic platform utilising AI algorithms for weed control in rice cultivation, which aims to enhance efficiency and reduce environmental impact. This approach integrates chemical and mechanical methods to effectively manage weeds in direct seeded conditions, with the following objectives.

This research is projected to significantly impact future efforts in developing and implementing a robotic platform with AI algorithms customised for weeding systems for rice and other crops in rice-based cropping systems. The primary contributions of this study are noted as follows:

- The robotics system uses high-resolution cameras to detect the weed flora.
- The AI component analyses data using machine learning algorithms to make precise recommendations for specific herbicide applications and weed removal. The device automatically adjusts spray rates based on the weed density, decreasing herbicide usage.
- Extensive field investigations were undertaken in various rice fields to evaluate the suggested technique's effectiveness.
- This study evaluates the system's accuracy, efficiency, and environmental impact in contrast to traditional farming approaches. The study also demonstrated that intelligent robotics systems can significantly reduce herbicide use while increasing crop yields.

## 1. Design methodology

The robot is designed to run in the rice field to control the diverse weed flora by precisely applying herbicide in the intra-row and cutting and incorporating inter-row weeds. The robot can reduce herbicide application, farm workers, and water consumption. These robots, designed to operate in wet and muddy situations, have the potential to improve rice production efficiency and sustainability significantly. Robots equipped with modern cameras and nozzles can apply herbicides precisely where needed, focusing on the weeds rather than the entire field. In rice fields, weed management is crucial. Robots intended for rice fields must be flexible to different field conditions and crop stages. (Shi et al., 2023). This versatility implies that the same robotic systems can remain effective without considerable alterations in aberrant weather conditions.

### 1.1. Design and fabrication of the proposed robot model

A robot chassis is a schematic diagram that depicts the technical representation of a robot's chassis or frame, as shown in Fig. 1. In the figure, the orthographic projection is employed to show (a) the main assembly view, (b) the top view, (c) the left side view, and (d) the focused mechanism view.

The robot consists of integrating many hardware components required for the proper operation of a mobile robot tasked with identifying and spraying herbicide at specific targets, as well as removing and decomposing weeds. The components include a high torque brushless DC worm gear reduction motor, weed and grass cutter, horizontal rotary blade, water pump, fog sprayer head nozzle, pneumatic connectors, a 5-volt DC relay, wheel assemblies, containers, web cameras, pipes, and the robot's body. Additionally, components like craws have been used to loosen and level soil. The NVIDIA Jetson Nano board acts as the system's control center, managing computation, networking, and hosting navigation and image processing applications. (NVIDIA, 2022). The HP w100 Camera has real-time imaging capabilities, allowing for photo gathering and analysis to target specific weed-infested areas for herbicide application.

The robot's chassis serves as the structural backbone, containing motors, wheel mounts, weed cutter, horizontal rotary blade, and batteries, allowing the Jetson Nano board to regulate its mobility. The central hub controls the weed cutter, which has movable joints for dynamic movement and may be adjusted in real-time, depending on field situations. The horizontal rotary blade is attached to the rear of the weed cutter to incorporate the removed weeds in the soil. Three tiny test examples of direct seeded rice fields were prepared on the Siksha 'O' Anusandhan University, Bhubaneswar, Odisha, India, agriculture

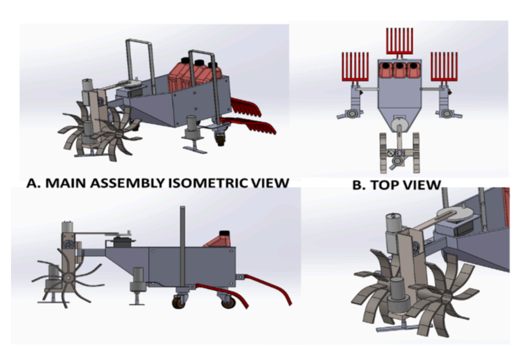



**Fig. 1.** The orthographic projection of the proposed robot.

farmland site, each measuring 100 $m^2$ area.

### 1.2. Implementation and Operational methodology

This section describes the system's architectural diagram, the programming procedure for weed identification and assessment, weed removal and incorporation mechanisms, the development of an instructional model for weed recognition, and the creation of a prototype model for system assembly. The weeding system, like removing and incorporating weeds in the field, uses robotic horizontal rotary blades, weed cutters, and nozzles. Fig. 2 shows the block diagram of the proposed robot system, which uses the Jetson Nano board as its system unit. The YOLOv5 model is trained on the Jetson Nano board and communicates with numerous units, including the motor, camera, weed cutter, horizontal rotary blade, and nozzle (Wang et al., 2022a) . A rechargeable battery with driving circuits controls the power. In direct-seeded rice, a spacing of 20 cm from row to row and 5 cm from plant to plant was maintained during sowing (Mahajan and Chauhan, 2016). Adhering to the recommended spacing, mechanical arrangements were constructed with a robotic chassis for variable gap correction based on real-time field situations. The system mechanics were built with nuts and bolts so that they may be adjusted up, down, and left to right based on real-world field conditions for weed control between the two rows of rice plants. Weeds were removed with grass cutter blades, and horizontal rotary blades incorporated the weeds inside the upper soil surface. As shown in Fig. 3 (a), the weedy plot with rice plants and a 20 cm gap is being cleared of weeds with the employment of the proposed robot. Three grass cutter blades and cultivators were employed to maximise the robot's efficiency, which can move in three rows at a time, as seen in Fig. 3 (b). The method intends to incorporate the weeds in the soil, which is left between the rows for decomposition, potentially increasing soil fertility, as seen in Fig. 3 (c).

The YOLOv5 model is trained and evaluated on images of various weeds. A set of models was explicitly created to identify and classify different weed types based on their visual characteristics (Dang et al., 2023). The details of the weed varieties are discussed in the following section.

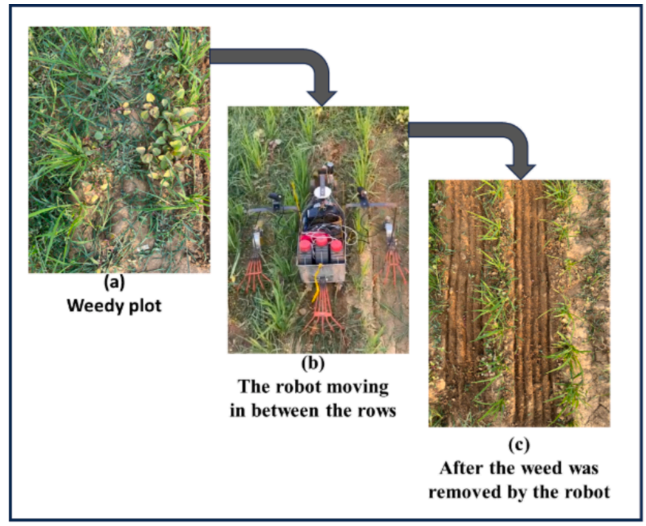



**Fig. 3.** (a) Weedy plot, (b) Robot moving in between the rows, (c) After the weed removed by the robot.

### 1.3. Weed flora composition training model for the system

Weeds were classified based on their morphology as grasses, broad-leaved, and sedges. Subsequently, weeds in the experimental field were identified using a validated database. This strategy relied on machine learning techniques (Vasileiou et al., 2024). A model was developed specifically to recognise and classify various weed types based on their visual characteristics. An extensive collection of images representing multiple weed species was employed to train this model, with each image labeled with the proper weed type. During the training process, the model had access to this dataset and the parameters controlling its learning and prediction algorithms. As the data was analysed, the model

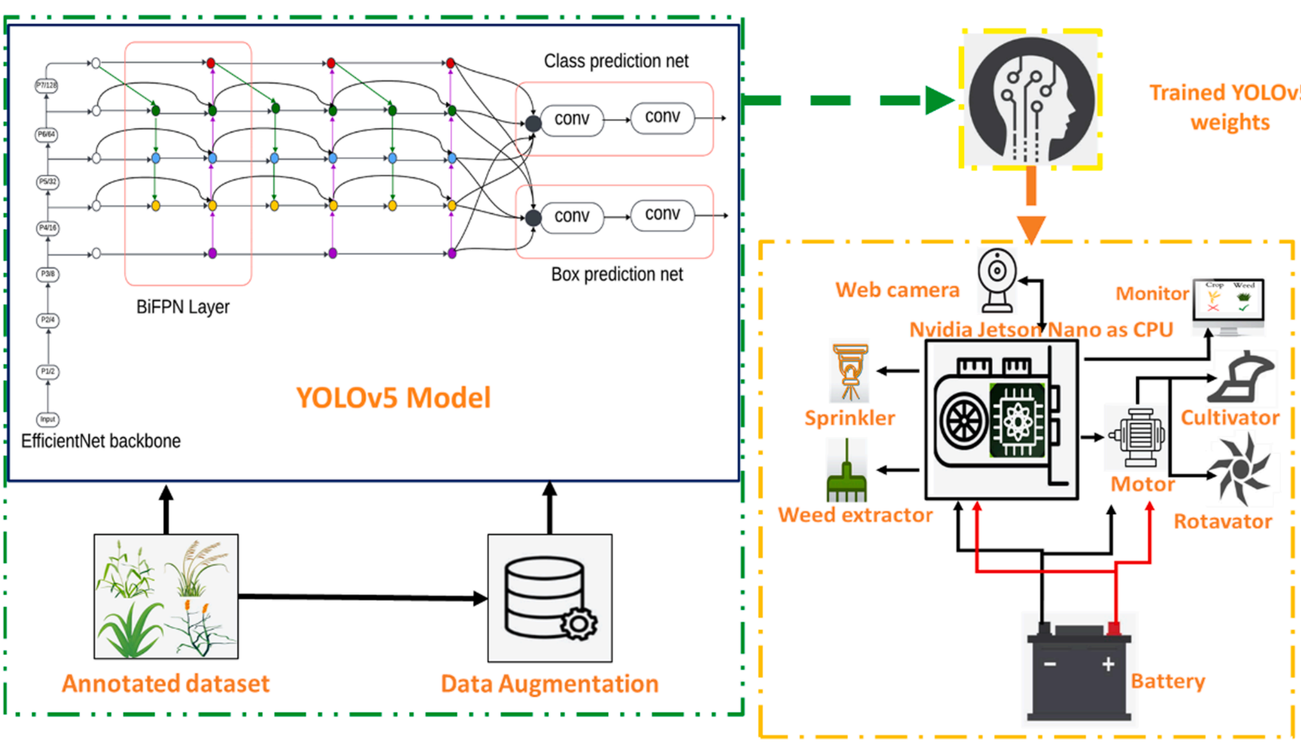



**Fig. 2.** Block diagram of the proposed robot system for the detection and evacuation of weeds.

learned to recognise various visual properties unique to different weed species, allowing it to categorise new images that it didn't recognise earlier. The training process involves introducing machine learning algorithms to a dataset containing images of weeds found on farms across various rice fields. (Sharma et al., 2021). These images were matched by labels identifying the weed species shown. At the sixty-day mark of the Kharif season, the experimental area was infested with a wide range of eleven predominant weed species, divided into three unique categories: five varieties of grass, five types of broadleaved, and two types of sedges, spanning seven families. The bulk of these species were monocots, with only four exceptions—Ludwigia parviflora, Melochia corchorifolia, Eclipta alba, and Alternanthera philoxeroides—identified as dicots. It's important to note that, even though being classified as broadleaved, some weeds, such as Commelina benghalensis, have monocotyledonous features. The distribution of weed dominance differed across treatments, as seen in Table 1. In the weedy check plots, all eleven weed species were present. During the crop growth phase, six significant weed species appeared regularly throughout the experimental field. Notable among these were Digitaria sanguinalis and Echinochloa colona from the grasses, Cyperus iria from the sedges, and Ludwigia parviflora, Melochia corchorifolia, and Alternanthera philoxeroides from the broadleaved weeds.

In direct-seeded rice, the significant weed flora were Digitaria sanguinalis, Echinochloa colona, Leptochloa chinensis, Panicum repens, Cyperus iria, Fimbristylis miliacea, Ludwigia parviflora, Melochia corchorifolia, Eclipta alba, Commelina benghalensis and Alternanthera philoxeroides (Rao et al., 2007; SANGRAMSINGH and DASH, 2021). Similarly, it also reported the dominance of Echinochloa sp. and C. iria in rice. (Awan and Chauhan, 2016; Garg et al., 2019). This dataset was used to train machine learning algorithms, resulting in a robust weed training model. A data set of images of weeds of various kinds, such as grasses, sedges, and broad leaves, was leveled and used to train the model shown in Fig. 4.

### *1.4. Deployment of an AI model to locate and spray pesticides on residual weeds near rice plants—post-robotic weed removal between rows*

A thorough investigation was conducted on various weeds and their growth at different stages. The recommended dose, time, and types of herbicide application to control specific weeds were considered. A comparison study was conducted on the use of several herbicides for controlling distinct weeds (Tu et al., 2003). Images of various weed species that grow in various soil conditions, such as upland, lowland, and medium land situations, were obtained from different parts of Odisha.

**Table 1**
Floristic composition of weeds in the experimental site.

| Botanical name | Family | Common name |
|---|---|---|
| Grasses | | |
| Digitaria sanguinalis (L.) Scop. | Poaceae | Large crabgrass |
| Echinochloa colona(L.) Link. | Poaceae | Jungle rice |
| Leptochloa chinensis(L.) Nees | Poaceae | Chinese sprangletop |
| Panicum repens L. | Poaceae | Dog-tooth grass |
| Sedges | | |
| Cyperus iria L. | Cyperaceae | Rice field flat sedge |
| Fimbristylis miliacea (L.) Vahl. | Cyperaceae | Hoorahgrass |
| Broadleaved weeds | | |
| Ludwigia parviflora Roxb. | Onagraceae | Water primerose |
| Melochia corchorifolia L. | Sterculiaceae | Chacolate weed |
| Eclipta alba (L.) Hassk. | Asteraceae | False daisy |
| Commelina benghalensis L. | Commelinaceae | Tropical spiderwort |
| Alternanthera philoxeroides (Mart.) Griseb. | Amaranthaceae | Alligator weed |

This configuration allows the robot to identify weeds autonomously using the weed training model; the weeds will be eliminated by the weed cutter and incorporated inside the soil by the horizontal rotary blade. The nozzles will spray herbicides as needed. Camera-based systems combining artificial intelligence, computer vision, and machine learning show promise for weed detection in rice fields, but they face significant challenges. These issues include the resemblance of rice and weeds, weather variations, the dynamic nature of crop-weed competition, limited availability of training data, and high computational needs. Considering the challenges presented in this test situation, the prototype model focuses entirely on machine-learning approaches. Over 1000 sample images were collected for each weed group to improve precision. The YOLOv5 Model was constructed and trained using a machine learning approach (Ajayi et al., 2023; (Wang et al., 2022c) ). Identifying weeds in rice fields using AI often involves several stages. YOLOv5 initially resizes an input image to a predetermined size to ensure consistency across all inputs (Lan et al., 2024). It uses a CNN backbone to extract features from the scaled image. Fig. 5 shows how the backbone is connected to other layers to form a feature pyramid. YOLOv5 has predefined anchor boxes, essentially shapes (width and height) that the model uses as references when predicting the bounding boxes of observed objects. Each location on the feature map predicts a bounding box relative to the anchor boxes.

A self-constructed dataset was developed using data collected from the agricultural firm land of SOA University, Odisha, India. The weed dataset comprises images of various weed species typically found in paddy fields, captured from different experimental plots in real-experimental setup conditions. For the second phase of dataset creation, image capture was performed on the experimental field using the robot equipped with an integrated camera. Data was collected multiple times in different lighting conditions to ensure an extensive dataset. Images captured by the robot in the experimental field were combined with images from other fields to produce a single dataset. The sample images used in the model align with the robot's shooting angles, ensuring consistency with the agricultural machine's real-world deployment. This was validated during the experimental setup. The fixed problems included format differences, noise, and unequal class distribution. This dataset was subsequently categorised based on distinct weed characteristics.

During the experiments, the real-time images acquired by the robot were compared with the self-constructed dataset to enable weed identification and eradication. Various techniques were employed to moderate these issues. Image augmentation, including transformations like rotation, scaling, and brightness adjustments, was utilised to simulate real-world variability and improve model robustness. Transfer learning was applied to fine-tune the YOLOv5 model using real-world test data collected by the robot, ensuring better alignment between training and deployment conditions. Additionally, feature extraction methods such as random search cross-validation (RSCV) and principal component analysis (PCA) were incorporated to enhance feature selection during training, enabling the model to adapt effectively to real-world scenarios. The detailed flow diagram of the fine-tuning of the YOLOv5 model is shown in Fig. 6.

Since multiple bounding boxes can be predicted around the same object, Non-maximum Suppression (NMS) helps in selecting the most accurate bounding box by eliminating overlapping boxes based on a confidence score threshold and Intersection Over Union (IoU) criteria as shown in Eq. 1.

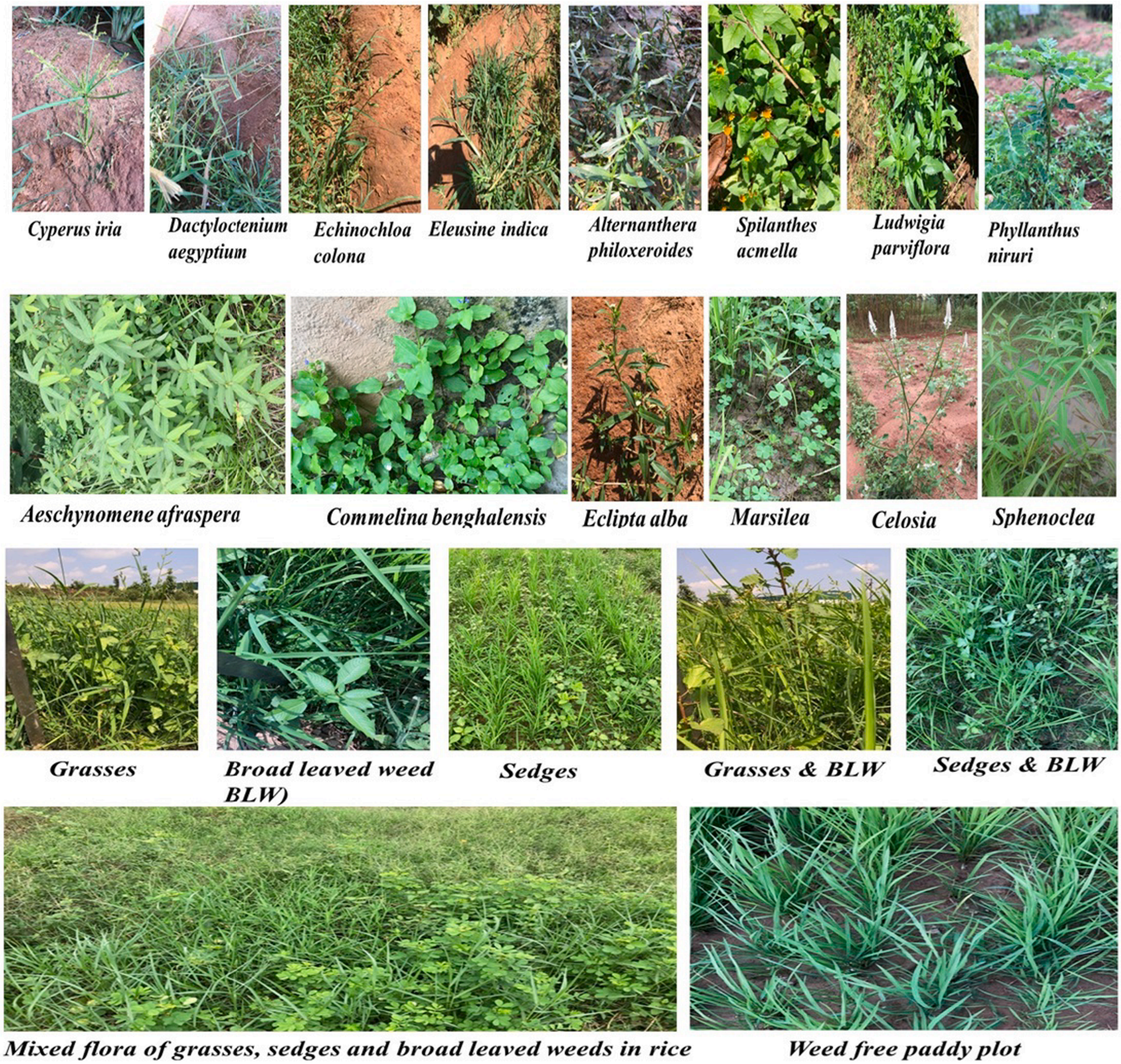
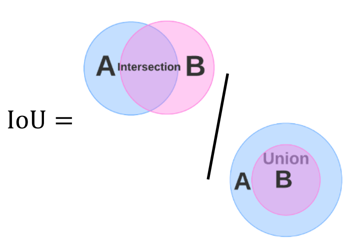



**Fig. 4.** Data sets of pictures of weeds of different categories, like grasses, sedges, and broad leaves.




(1).

Where A and B are convex shapes, the analysis includes determining the number of true positives. A predicted bounding box is called true positive if it overlaps a ground truth bounding box with an Intersection over Union (IOU) threshold of 0.5, showing that the detection was successful. However, if a predicted bounding box overlaps with a ground truth bounding box below the threshold, it is considered a false positive and an unsuccessful detection (Karthi et al., 2021). The precision and recall metrics can then be calculated based on the true positives and false positives using the following formulas:

$$\begin{aligned}\text{Precision} &= \text{True positive}/\text{True positive} + \text{False positive}\\ &= \text{Count}(\text{True positive})/\text{Count}(\text{True positive} + \text{False positive})\end{aligned} \tag{2}$$

$$\begin{aligned}\text{Recall} &= \text{True positive}/\text{True positive} + \text{False negative}\\ &= \text{Count}(\text{True positive})/\text{Count}(\text{True positive} + \text{False negative})\end{aligned} \tag{3}$$

If the predicted bounding box differs from any of the image's target classes, consider it a false positive. If the expected class corresponds to one of the target classes, compare the estimated bounding box to the target boxes in the images. Use the IOU threshold to determine the maximum overlap between the predicted and target bounding boxes. If the most significant overlap exceeds the IOU threshold, indicate that the target box has been successfully detected and the predicted bounding box is a true positive (Jiang et al., 2021). If the most significant overlap is less than the IOU threshold, mark the bounding box as a false positive. The F1 score determines the ideal level of confidence threshold that balances precision and recall. A higher F1 score indicates more precision and recall (Urmashev et al., 2021).

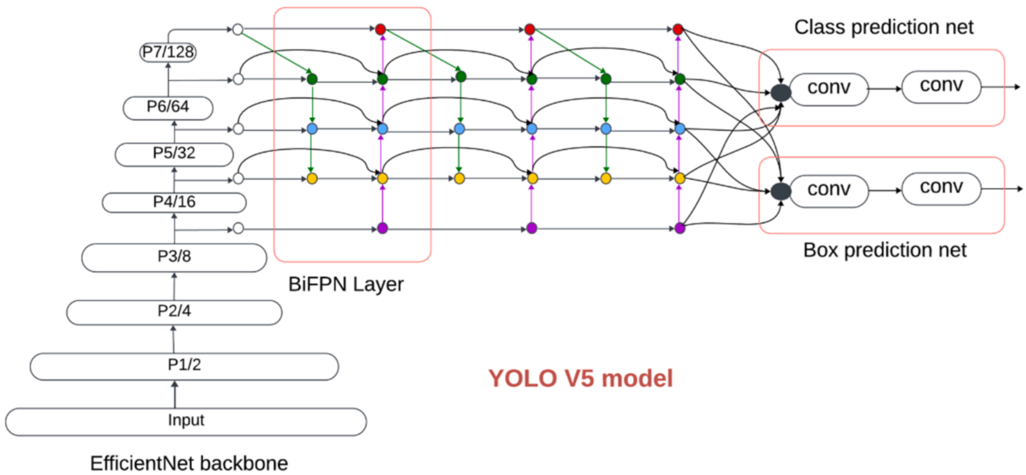



**Fig. 5.** The YOLOv5 architectural block diagram shows EfficientNet as the backbone network, BiFPN as the feature network, and the class/box prediction network.

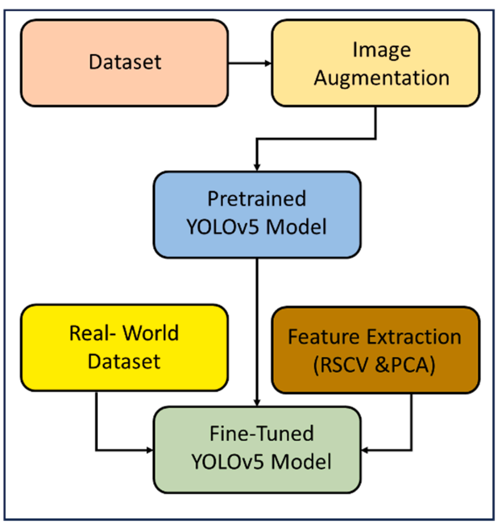



**Fig. 6.** Flow diagram of the fine-tuning of the YOLOv5 model.

$$\text{F1 Score} = 2 \times (\text{precision} \times \text{Recall})/(\text{precision} + \text{Recall}) \tag{4}$$

The YOLOv5 model has several modifications and optimisations to improve its suitability for agricultural applications. Custom anchor box tuning was implemented to enhance the detection of small objects, such as narrow weed patterns, under real-world field conditions. The model's performance was further refined by incorporating test data collected by the robot and combining it with real-world data, ensuring improved accuracy in practical deployments. YOLOv5's lightweight architecture, optimised for embedded devices, facilitated smooth deployment on platforms like NVIDIA Jetson Nano. Data augmentation is a critical technique in this deep learning, particularly in training models like YOLOv5 for object detection. The model was integrated into the system and applied to the test case rice field. Mosaic augmentation is particularly interesting and compelling for object detection tasks for this rice model (Dai et al., 2022; Dang et al., 2023; Xu et al., 2024). In a single training instance, a mosaic combines four different training images into one composite image. These images are randomly selected from the dataset. The four images are placed such that each one occupies one quadrant of the new composite image. Each object's bounding box coordinates in the original images are adjusted relative to their new position in the composite image. Fig. 7 illustrates how the YOLOv5 model detected weeds and generated predictions according to their classification, compared with the weed training model.

Fig. 8 shows a system flow chart. Following deployment, the AI model's performance was continuously monitored. Refinements were made as needed to improve the model's accuracy, and it was adjusted to changing conditions in the rice fields. After 300 Epochs of training, the model achieved a reasonable level of accuracy. The Nvidia Jetson Xavier GPU performed well at object detection at 30 fps, allowing commands to be sent to motors, cutters, and nozzles. The camera in the robot recognises weed species and compares them to a database. The specific herbicide will be applied to the weed plant following weed identification. At the same time, in mixed-flora conditions, broad-spectrum herbicides will be used to control weeds successfully.

The herbicides listed in Table 2 are employed to control both specific and broad-spectrum weeds in this test case scenario (Bhullar et al., 2013). Three different containers were pored with appropriate herbicide dosages and attached to six 12-volt DC pumps. The entrance was in the container, and the exit was connected to two fog sprayer head nozzles facing opposite directions using pneumatic splitter connectors. Fig. 9 shows the logic diagram for pneumatic control.

However, in the conventional approach, herbicide is sprayed on an area basis without concern for the presence or absence of weeds. The amount of herbicide used in the traditional approach is fixed, resulting in excessive use and soil and plant health degradation (Mandal et al., 2020; Parven et al., 2024; Perotti et al., 2020; Tripathi et al., 2020). When compared to traditional rice cultivation methods, this robot can save on herbicides and labour (Fennimore and Cutulle, 2019). This herbicide spraying is restricted to the crop row zone only. Weeds between the rows are controlled using a motor-operated weed cutter, which cuts down the weeds in the exact location (Loddo et al., 2020). In Fig. 11, three images are provided which illustrate the weeds after the robot evacuation left surrounding the rice plant after a few hours of herbicide spraying and, after ten days, the decomposed weeds.

### *1.5. Deployment of remote observation and manual operation for weed eradication*

In this proposed test case scenario, the jetson nano board can connect to the internet via a Wi-Fi system, and a local host has been set up to view a live preview of the robot's cameras. The manual cross-check method has also been used to ensure that the automated robotic system has removed the weeds in the rice field. A laptop or smartphone may control the robot, and if any weeds remain, as visible in the live camera preview, the robot can be stopped and herbicide applied to the infested area. The system is designed to allow the farmer to operate and double-check his work from any remote location, as the camera preview can also be viewed online. The block diagram of the suggested model is presented in Fig. 10.

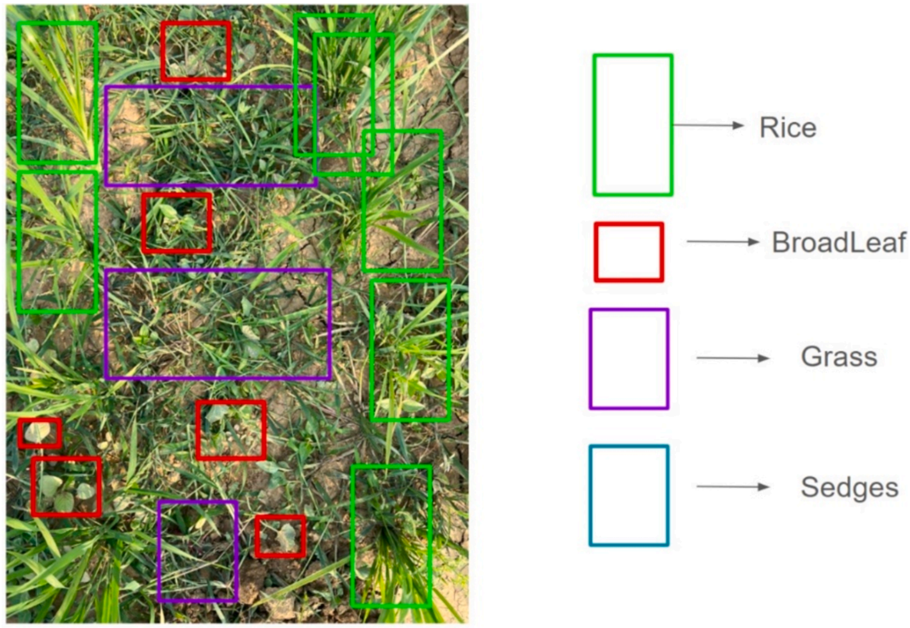



**Fig. 7.** YOLOv5 object detection by the proposed robot mount view of weeds and rice.

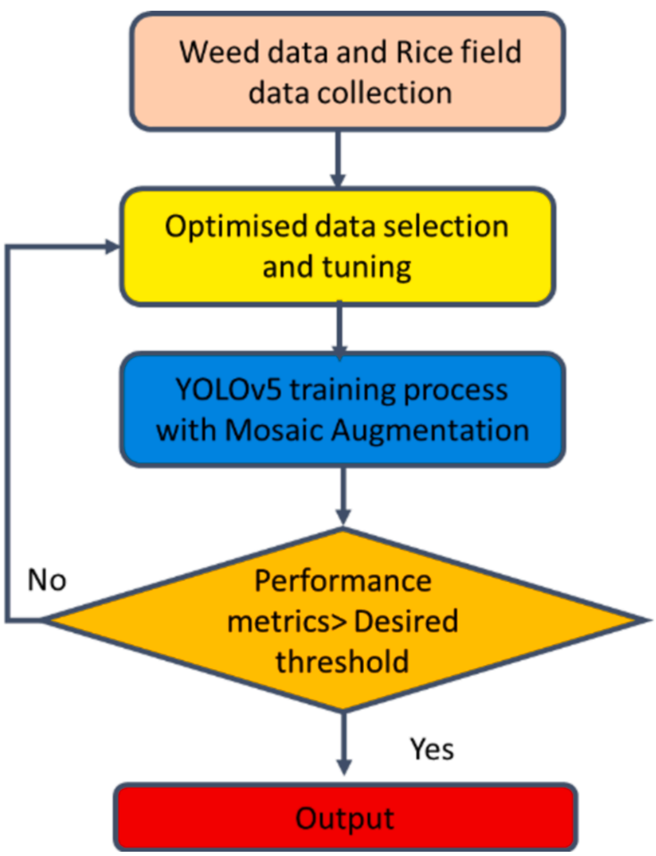



**Fig. 8.** System flowchart of the YOLOv5 model for the proposed robot.

**Table 2**
Herbicides used in direct-seeded rice to control diverse weed flora in conventional farmer's practice.

| Herbicide Name | Formulation | Dose (g) (a.i. per ha) | Dose (lt.) (actual amount to be sprayed) | Dilution In Water (litres) | Remark |
|---|---|---|---|---|---|
| Bispyribac Sodium | 10 % SC | 25 | 250 | 300 | Broad-spectrum weed control |
| 2,4-D Ethyl Ester | 38 % EC | 750 | 1973 | 400 | Effective against broad-leaved weeds only |
| Fenoxaprop-p-ethyl | 6.7 % EC | 60 | 895 | 500 | Effective against grasses only |

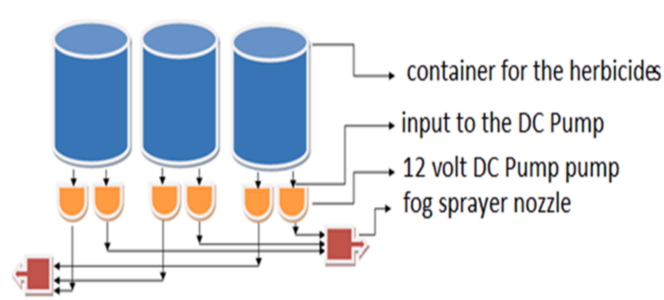



**Fig. 9.** The logic diagram of the pneumatic control.

## 2. Results and discussions

### 2.1. Assessment of the prototype

A thoroughly selected set of performance measures was used to test the effectiveness of the weed detection, removal, and incorporation system prototype. To extensively test the system's capabilities, a series of real-world scenarios were designed to assess its ability to recognise and eliminate weeds in a variety of environmental circumstances. To ensure experimental integrity and reduce external influences, a controlled test environment was rigorously designed to simulate future deployment settings accurately. Throughout the testing phase, a vast amount of data was meticulously collected, including critical


**Fig. 10.** Effect of proposed robot application in the rice field.

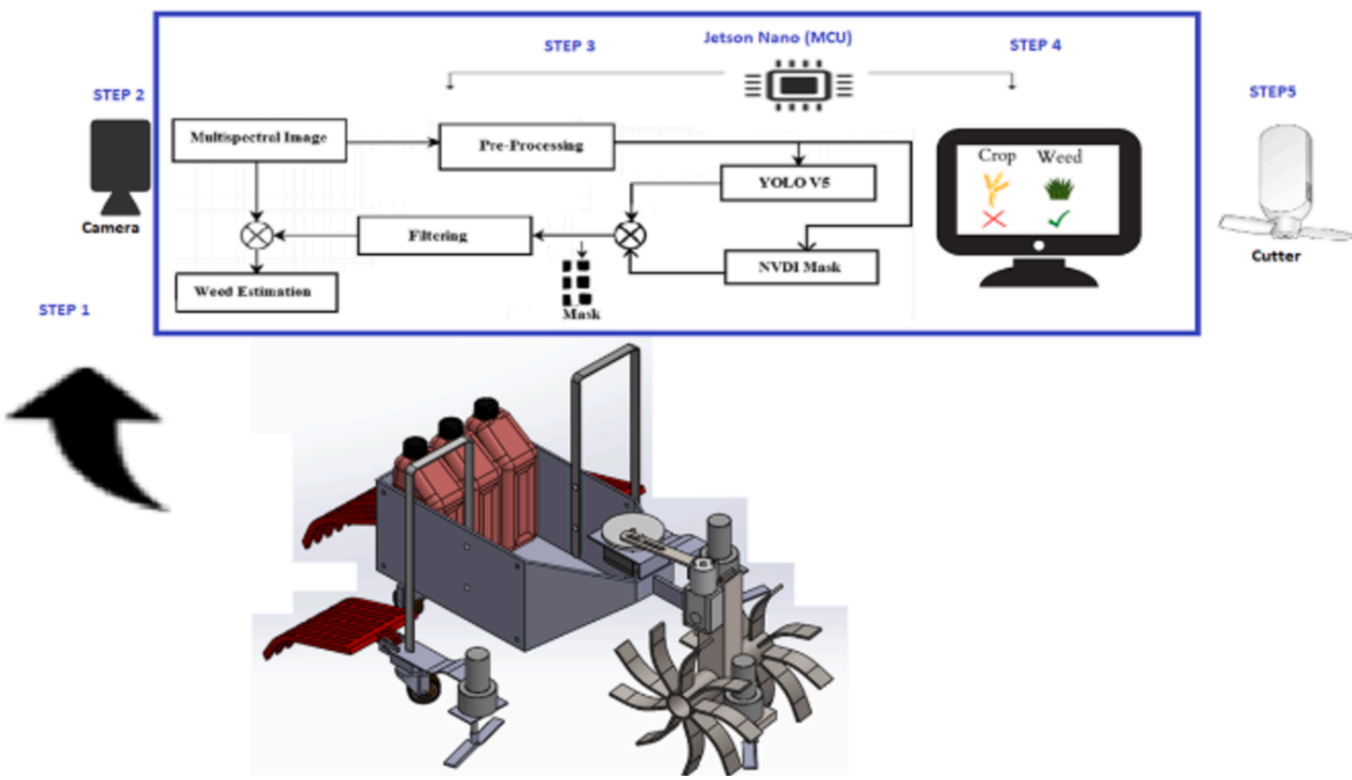



**Fig. 11.** Prototype model of the proposed robot.

parameters such as the rate of weed identification, the time necessary for evacuation, and the effectiveness of incorporation processes. The following analysis of this data enabled a detailed evaluation of the prototype's performance, determining specific areas that need modification in accordance with specified objectives.

### 2.2. Comparisons study with respect to accuracy, precision, recall and F1 score

According to (Li et al., 2022) , the weed detection and spraying system (Model-1) achieves a high accuracy of 0.93 in real-time detection and classification of weeds and crops, ensuring minimal misclassification. Model-1 demonstrates a precision score of 0.94, effectively minimising herbicide waste by targeting detected weeds, and a recall score of 0.91, highlighting its ability to identify a diverse range of weed species, even in complex or overlapping scenarios. The F1-score of 0.92 reflects a balanced trade-off between precision and recall, affirming its reliability for precision agriculture. In comparison, (Liu et al., 2021) report that their weed detection and spraying system (Model-2) achieves an accuracy score of 0.97, a precision score of 0.89, a recall score of 0.87, and an F1 score of 0.88. The proposed model outperforms both, with an accuracy of 0.98, precision of 0.93, recall of 0.91, and an F1-score of 0.92. A comparative analysis of Model-1, Model-2, and the proposed system is illustrated in Fig. 12. The robot has the watch and spry facilities in the proposed model, like Model-1 and Model-2. The additional weed evacuation facility in the proposed model shows better accuracy,

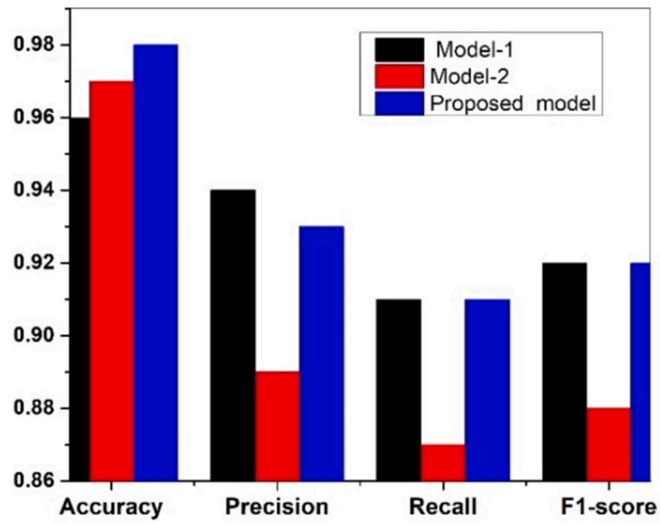



**Fig. 12.** Comparisons of model-1, model-2 and the proposed robot model with respect to the accuracy, precision, Recall and F1 score.

precision, recall and F1 results. The proposed robotic system enhances rice crop health by ensuring precise and thorough weed control by reducing competition for vital nutrients, water, and sunlight, thereby boosting yields. Its consistent and efficient operation addresses critical agricultural challenges, contributing to food security while reducing reliance on manual labour and excessive chemical use.

The weed training model was thoroughly evaluated, considering accuracy, precision, recall, and F1-score while using images from rice fields. Notably, the algorithm achieved an accuracy level of 0.98, showing its ability to classify weeds and crops correctly. Data augmentation, transfer learning, and incorporating domain expertise each served to improve the model's strength and generalisation capabilities. As a result, the weed training model is critical in increasing rice yield by efficiently controlling weeds, allowing for more effective weed management. The Weed25 dataset was trained by the YOLOv3, YOLOv5, and Faster R-CNN models for weed identification, where the precision was 91.8 %, 92.4 %, and 92.15 %, respectively (Wang et al., 2022b) . Using training models in weed management significantly enhances crop yields by optimising weed control methods, thus promoting the application of intelligent weed control technology in practice.

### 2.3. Weed detection and control accuracy

A comparison of manual labour, traditional farming methods, and the proposed robot model for weed control was carried out. Manual labourers were engaged in hand weeding to control weeds, while conventional methods involved farmers using knapsack sprayers to apply herbicides. The results showed that the proposed technology was more efficient than manual approaches, covering more territory and incorporating a more significant number of weeds per hour.

The proposed prototype of a weed identification and evacuation robot was rigorously tested, and the results are shown in Fig. 13. The robot demonstrated its effectiveness in weed control by comparing physical labour and traditional farming methods. The proposed robot demonstrated exact precision, recognising and removing weeds with an error margin of only 2 %. The costs of robotic weed management were high. Still, robotic weeding was a robust and effective weed control method with great potential to save herbicides in arable and vegetable crops (Fennimore et al., 2016; Gerhards et al., 2024; Monteiro and Santos, 2022). In comparison, manual approaches were shown to be 1.2 times slower in controlling weeds. Furthermore, the robot demonstrated a superior weed control rate, exceeding 95 %. In addition, the system's performance was assessed based on weed control rates, which showed

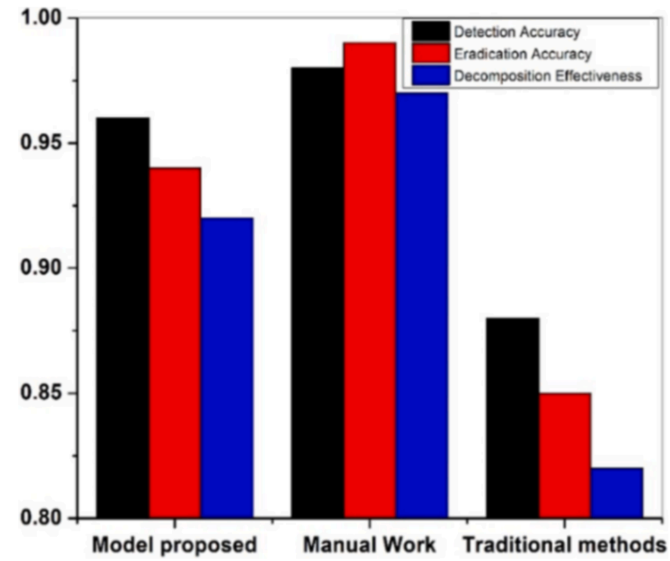



**Fig. 13.** Comparative analysis of manual labour and traditional farming methods with the proposed robot.

an excellent incorporation rate of more than 90 %. Further, the system's interoperability with existing agricultural practices and equipment has the potential to reduce costs and labour while enhancing yield and profitability significantly. In particular, the robot's ability to resist various weather conditions and rugged terrains and operate with little maintenance requirements highlight its usefulness and relevance for agricultural applications (Kumar et al., 2023). It is also relatively safer and eco-friendly than the indiscriminate use of chemicals to control diverse weed flora in direct-seeded rice cultivation.

### 2.4. Evaluation analysis

Fig. 14 shows the performance metrics of the evaluation analysis for cost and scalability in terms of weed control in real-time scenarios in the proposed model. This is an essential indicator for determining its effectiveness.

These criteria were critical to the robot's comprehensive weed detection and removal assessment. This evaluation analysis shows that the model is faster and more accurate than conventional methods. As a result, the use of this advanced technology in agricultural fields replaces

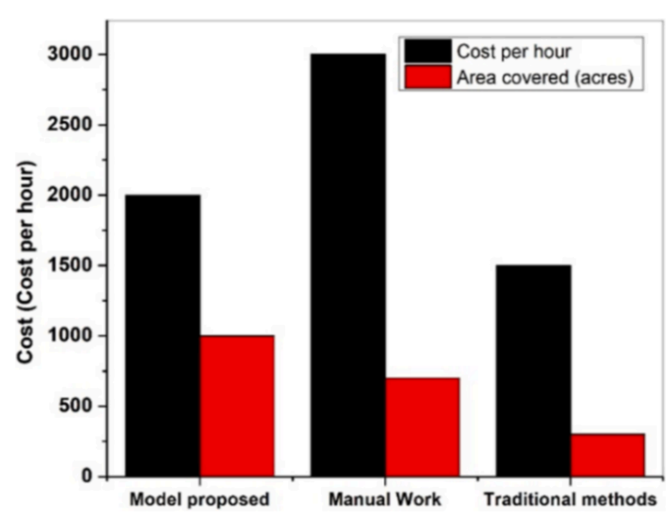



**Fig. 14.** Evaluation analysis (cost-effective and scalability with respect to weed and herbicide management in real-time scenarios).

the over-reliance on herbicides and traditional farming machinery, providing a more efficient and sustainable approach to weed management (Esposito et al., 2021).

## 3. Conclusion

The weed detection and removal prototype, augmented by an AI model, was methodically designed to accurately identify, remove, and incorporate weeds in rice fields. The AI system is constantly improved to enhance weed detection, removal accuracy, and speed. To increase the model's robustness and dependability, it might be trained on a more diversified dataset containing various weed species under different conditions. The experimental results showed that the model has the potential to improve agricultural output, efficiency, and cost-effectiveness significantly. It improves the proposed robot's design and functioning, allowing it to operate in various terrains and weather situations. This may involve increasing the durability and energy efficiency of the robots. The key advantage of the YOLOv5 model is its training efficiency, requiring fewer computational resources compared to more recent models such as YOLOv8 or YOLO-NAS. YOLOv5 is well-suited for edge-devices deployment, including NVIDIA Jetson modules, Raspberry Pi, and mobile platforms, often offering better integration than newer architectures. At the same time, these latest models demonstrated higher accuracy in isolated experiments. Future work will focus on integrating advanced architectures like YOLOv8 or YOLO-NAS to enhance performance in subsequent iterations. More advanced machine learning approaches could allow the system to adapt dynamically to new settings and optimize its real-time decision making processes. Moving in advance, it is critical to investigate potential enhancements, incorporate new approaches, and ensure compatibility with existing facilities. This strategic approach will improve the system's adaptability and scalability while ensuring its applicability across various soil types and environmental circumstances. Engaging with farmers, scientists, and agricultural technicians to ensure that the technology meets practical field needs and encourages adoption through field demonstrations and trials, as well as continuously assessing the technology's environmental impact to ensure that it contributes positively to sustainable farming practices, such as reducing chemical usage and minimising soil health degradation. By addressing these issues, the prototype robot may be transformed into a reliable system that fulfills present expectations and is also future-proofed to adapt to changing agricultural practices and issues. This deliberate, comprehensive strategy will contribute to the technology's success and widespread acceptance in agriculture.

## CRediT authorship contribution statement

**Tirthankar Mohanty:** Writing – original draft, Software, Resources, Data curation. **Priyabrata Pattanaik:** Writing – original draft, Supervision, Formal analysis, Conceptualization. **Subhaprada Dash:** Project administration, Investigation. **Hara Prasada Tripathy:** Writing – original draft, Visualization. **William Holderbaum:** Writing – review & editing, Supervision, Investigation.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [NA If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper].

## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2025.110032.

## Data availability

No data was used for the research described in the article.

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