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Development of a Weeding Agrobot Prototype for Inter-row and Intra-row Weeding

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ABSTRACT

Background: India faces a critical shortage of farm labour. Out of basic farming operations, weeding operations are not fully mechanized in India. Traditional weed control methods are tedious, labour-intensive and costly.

Methods: The objective of this study was to develop a prototype of an autonomous weeder for inter and intra-row weeding. The materials were used include a DC motor operating on electric rechargeable batteries, a camera for taking photographs of the intra-row space, an inter-and intra-row weeding tool assembly, a Raspberry Pi to deploy a machine learning object detection model to detect weeds and crops, to control a motor and to control an intra-row weeding tool through the pneumatic actuator. While the intensive image dataset was prepared from a cultivated spring onion farm on a test soil bin over the University campus, moreover the small-sized YOLOv8n model worked accurately on the Raspberry Pi.

Result: YOLOv8n achieved a mean average precision (mAP) of 0.85 at the Intersection of the Union (IoU) threshold of 50%. The results indicated that the prototype removed both types of weeds with an overall weeding efficiency of 86%, crop damage of 4%, a field capacity of 0.023 hectares per hour and a performance index 1726.26 using 0.11 horsepower. It was concluded that the study contributed a spring onion-weed dataset and a Weeding Agrobot prototype to test the described concept, which would help farmers reduce labour dependency and the cost of cultivation.

Key words: Autonomous weeder, Machine learning, Prototype, Raspberry Pi, Weeding, YOLOv8n.

INTRODUCTION

There is a critical farm labour shortage and limited machinery usage in India. Weeding removes undesirable plants from fields, which compete with crops for living, reducing yield and crop quality. Inter-culture or weeding operations are not fully mechanized. Mechanical weeding is preferred over manual and animal-drawn methods, which are labour-intensive. In India, available weeders mainly remove inter-row weeds, which are costly and not autonomous. Oversized machines are unsuitable for average farm sizes and cropping patterns. In recent innovations, laser technology or weedicide sprayers have been integrated into weeders. An intra-row weeding system was developed based on mechatronic techniques (Kumar *et al.,* 2024). The performance of a self-propelled diesel engine equipped with three-blade sets, designed for intra-row weeding in vegetable fields, was evaluated (Khayer *et al.,* 2024). The performance of the power weeder was assessed in sugarcane crops under various conditions (Mohan *et al.,* 2020). An e-powered mechanical inter-row weeder has been developed for small farms (Pandey *et al.,* 2023). The performance of a battery-operated power weeder was assessed in a soybean crop (Pandey *et al.,* 2021). The integrative weed management treatments on growth attributes were evaluated (Bandyopadhyay *et al.,* 2024) and effect on rice (Kashyap *et al.,* 2022) and overall productivity of crops was studied (Meena *et al.,* 2022). A lightweight weed detection mechanism for laser-weeding robots was developed using crop-weed datasets, achieving a mean Average Precision of 0.88 and 0.53 at an Intersection over Union (IoU) of 0.5 with YOLO5 and SSD-ResNet50 models, respectively (Fatima *et al.,* 2023). RetinaNet and YOLOv5n reached mAP of 79.98% and 76.58% in the cotton field, as mentioned by Rahman *et al.* (2023).

Due to the gaps, such as labour dependency, unsuitable size and high cost of the available weeders and unavailability of intra-row weeders, the objective was to develop a compact, low-cost, efficient, autonomous, environmentally friendly weeder for inter- and intra-row weeding to assist small farmers. The research objectives include identifying gaps in the present study, developing a prototype of an autonomous weeder for inter-row and intra-row operations and testing the prototype in a sample soil test bin to validate the concept.

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MATERIALS AND METHODS

The present work was carried out at the Department of Instrumentation and Control Engineering, COEP Technological University, Pune, Maharashtra, India, for period of three years from 2022 to 2025. Considering the Indian farming conditions, a prototype of an autonomous weeder is developed through the steps mentioned as follows.

Dimensional design of an autonomous weeder prototype

Fig 1 (a) represents the dimensional scenario of the Agrobot, along with the assumed dimensions of the inter-row and intra-row spaces, 300 mm and 150 mm, respectively, Fig 1 (b) shows the actual onion field on the test soil bin and Fig 1 (c) represents an actual prototype.

Motor selection

The total force is the summation of the rolling resistance force, aerodynamic force and acceleration force. Assuming the motor efficiency is 85%, the power required is 0.4 kW for muddy and 0.6 kW for sandy soil. An electric brushless direct current BLDC motor with the criteria 0.6 kW < Motor power and 350 < Motor rpm was selected to move the weeder.

Design in CATIA and stress analysis in ANSYS

The mechanical frame structure was designed using CATIA software and stress analysis was done using ANSYS software (Fig 2a, 2b). When 250 N was applied, the maximum stress and deformation observed were 7.8 MPa and 0.11 mm, respectively.

Components of the weeder

1. **Frame:** Made of mild steel (MS), affordable, weldable and machinable.
2. **Four wheels:** The front wheels are bike tyres and the rear wheels are small activa tyres. The motor is attached to the front wheels through a chain drive-pull and conveyor belt.
3. **Web camera:** Zebronics zeb-crisp pro web camera (HD), mounted vertically on the frame to create a database for machine learning.
4. **Pneumatic cylinder, actuator:** The pneumatic cylinder and actuator, controlled by a Raspberry Pi, operate on 24V and 12V, respectively, to control a centrally connected weeding tool.
5. **Battery:** 48V (Four 12V lead-acid rechargeable batteries in series).

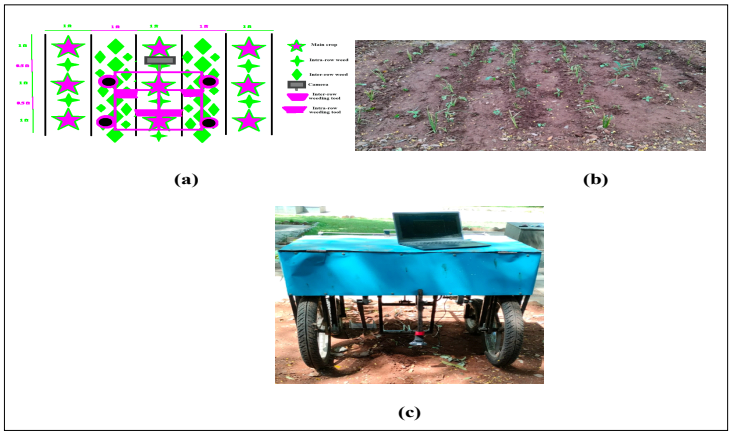


Fig 1: (a) Dimensional design of weeding agrobot prototype; (b) Actual onion field on test soil bin; (c) Prototype of weeding agrobot.

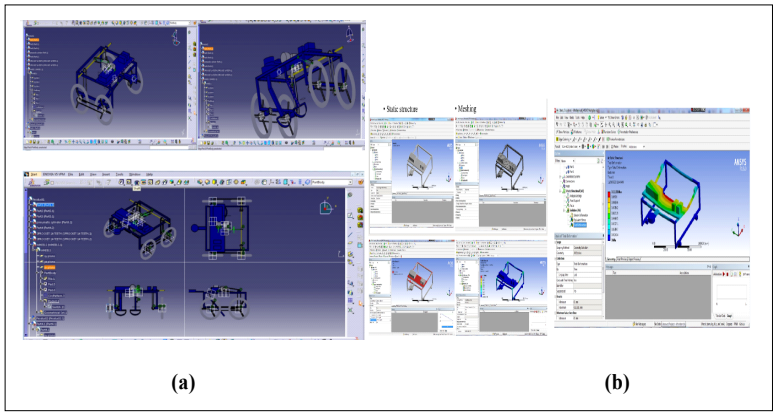


Fig 2: (a) CATIA design; (b) Testing in ANSYS.

6. **Raspberry Pi 4B+:** This device has a 64-bit quad-core processor, 8GB of RAM, moderate power consumption, high processor speed, multimedia performance, memory and connectivity.
7. **Inter-row, intra-row weeding tools:** Two centrally located intra-row weeding tools and two both-sided inter-row weeding tools (HO-M15 Bow, WOLF-GARTEN tools) are market-available.

Dataset collection, data preparation and building a machine learning model

A spring onion farm was cultivated to prove the concept and conduct trials. After many object detection models were tried, the best model was chosen.

Spring onion cultivation

Spring onions are vulnerable to weeds due to their gradual early development and lack of adequate foliage to cover the ground, which hinders weed growth. The spring onions were grown in the designated test soil bin in the University area, with an inter-row spacing of 300 mm and an intra-row spacing of 150 mm. The plants grown on the farm other than the onion crop were assumed to be weeds. Table 1 shows the details of the test soil bin.

Dataset preparation

RGB images of weeds and spring onions were collected using a Python program developed on Raspberry Pi and a USB web camera positioned 150 mm above the ground while traversing the soil bin. The web camera captured images of 640 × 480 pixels. Photographs of 2600 × 4624 pixels, taken with a mobile phone camera, were added to enhance the dataset's diversity. All photographs were taken on sunny, cloudy and windy days, in dry and wet soil conditions, encompassing the growth stages from planting to harvesting and saved in .jpg format (Fig 3a-3d). Out of 5,000 images, including blurred photos, duplicates and those without onions or weeds, were removed for better accuracy.

Object detection models

Convolutional neural networks (CNN) consist of input, convolutional, pooling and flattened layers and they use tensors as the foundation for object detection. The transfer learning leverages weights from pre-trained models to improve performance with minimal custom data. LabelImg software was utilized for image annotation. The dataset was split into training, testing and validation sets in ratios of 80%, 10% and 10%, respectively. A balanced dataset was used for two classes: onion and weed. EfficientDetD0, MobileNetV2 SSD, MobileNetV2 SSD FPN-Lite, YOLOv8s and YOLOv8n were trained through varying epochs.

Development of a python code and deployment of a Machine learning model on raspberry Pi

The following functionalities are added by preparing the code in Python on the Raspberry Pi:

1. **PWM (Pulse width modulation) signal generation for motor control:** GPIO pin 18 was used as the output to control the 48V DC motor by generating a pulse width modulation (PWM) signal. The PWM duty cycle is used to vary the motor speed by controlling the motor terminal voltage (Katsambe *et al.,* 2017).

$$\text{Duty cycle (\%)} = d = \frac{t_{ON}}{T} \times 100 \quad \text{....(1)}$$

$$\text{Time period} = T = \frac{1}{\text{Frequency of PWM}} \quad \text{....(2)}$$

$$V_{out} = d \times V_{in} \quad \text{....(3)}$$

Where,
t_{ON} = 'ON' time.
T = Duration of one period = $t_{ON} + t_{OFF}$.
V_{in} = Voltage supplied to the motor.
V_{out} = Voltage after duty cycle is applied.

2. **Program for controlling a pneumatic cylinder and actuator through relays (for controlling an intra-row weeding tool):** GPIO pins 21 and 26 were used as outputs from the Raspberry to input a control signal to two relays that control the pneumatic compressor and actuator, which operate at 12V and 24V, respectively.
3. **Image capturing:** One program was deployed on the Raspberry Pi to capture and save pictures every second from a continuous video stream captured by the webcam.
4. **Deployment of best-suited machine learning model on Raspberry Pi:** Google Colab facilitates the training, conversion and export of TensorFlow Lite and PyTorch models.

Evaluation of the system

Evaluation of object detection models

Precision refers to the proportion of accurate predictions relative to the total number of predictions made. Recall signifies the ratio of correct predictions to the number of relevant objects present. Average precision (AP) is the area beneath the precision-recall curve, illustrating the trade-off between precision and recall. In mAP, the predicted bounding boxes from the model are compared against the ground truth annotations. The mean of the average precision (AP) across all classes and various Intersections over Union (IoU) thresholds is taken to compute it.

Evaluation of the proposed weeder

The following are the evaluation parameters of the weeder that involve evaluating its quality and quantity of work and the power used:

1. **Width of the operation:** The total width of inter and intra-row weeding tools.
2. **Depth of operation:** The vertical distance measured from the top of the soil surface to the base of the excavated area using a steel scale.

3. Speed of the weeder: The ratio of distance travelled by the weeder to the time required.

$$\text{Speed in m/s} = S = \frac{\text{Distance travelled}}{\text{Time}} \quad ...(4)$$

Adjusting the code's PWM duty cycle can set the weeder's speed. The speed was calculated using a stopwatch, considering the time required to travel a 10 m distance.

4. Theoretical field capacity (TFC in ha hr^{-1}): The machine's theoretical field capacity refers to how much ground it can cover, assuming it operates at full speed and utilizes its entire rated width without downtime (Devojee *et al.,* 2019).

Theoretical field capacity, ha h^{-1} =

$$TFC = \frac{\text{Width (m)} \times \text{Speed (km/h)}}{10} \quad ...(5)$$

5. Actual or effective field capacity (EFC in ha hr^{-1}): The area weeded during each trial run within a specified time interval was recorded to calculate the weeder's Effective field capacity using a stopwatch (Devojee *et al.,* 2019).

Effective field capacity =

$$EFC \text{ (ha h}^{-1}) = \frac{\text{Area of land weeded (ha)}}{\text{Time required (h)}} \quad ...(6)$$

6. Field efficiency (%): Field efficiency is the ratio of effective field capacity to theoretical field capacity.

$$\text{Field efficiency (\%)} = E_f = \frac{EFC}{TFC} \times 100 \quad ...(7)$$

7. Weeding efficiency (%): The ratio between the number of weeds removed by the prototype weeding agrobot and the number of weeds in a unit area, expressed as a percentage. The average of the three trials was taken.

$$\text{Weeding efficiency} = WE\ (\%) = \frac{W_1 - W_2}{W_1} \times 100 \quad ....(8)$$

W_1 and W_2 are the number of weeds counted in a specified area before and after the weeding operation. The average of inter-row and intra-row weeding efficiency is used to calculate weeding efficiency.

8. Plant damage (D%): The ratio of the number of plants/crops damaged after the weeding operation in a row to the number of plants present before the operation is calculated as follows:

$$\text{Plant damage} = D(\%) = \frac{P_1 - P_2}{P_1} \times 100 \quad ....(9)$$

P_1 and P_2 are the number of crops counted in a 10 m row field length before and after the weeding operation. The plant damage primarily arises from insufficient crop spacing, delays between weed detection and the operation of the weeding tool and inaccuracies in the machine learning model. Plant survival is calculated as follows:

$$\text{Plant survival (\%)} = 100 - D \quad ....(10)$$

9. Performance index (PI): It is directly related to the field capacity (ha/hr), plant survival and weeding efficiency (%) and is inversely associated with power (hp) input (Balas *et al.,* 2023).

Performance index per hour =

$$PI \text{ (ha hp}^{-1}) = \frac{EFC \times WE \times (1 - D)}{P} \quad ....(11)$$

Where,

EFC = Effective field capacity (ha hr^{-1}).

WE = Weeding efficiency (%).

D = Plant damage (%).

P = Power used in hp.

Power input to the weeder can be calculated as follows (Sahu *et al.,* 2017):

Power =

$$P(hp) = \text{Draft} \times \text{Speed} \times 0.0013 \text{ (conversation factor)} \quad ....(12)$$

Where the draft can be calculated as follows:

Draft (N) =

$$\text{Width of the cut (cm)} \times \text{Depth of the cut (cm)} \times \text{Specific soil resistance (N cm}^{-2}) \quad ....(13)$$

The black soil's specific resistance is 0.4 kg cm^{-2} (3.924 N cm^{-2}).

Working flow

When the switch is ON, the motor starts running, so the weeder begins moving. Inter-row weeding blades on both sides will remove inter-row weeds as the weeder moves. Simultaneously, the camera mounted on the weeder will capture photos of the intra-row space. The machine learning model deployed on the microcontroller will differentiate the main crop from weeds. Until the weeds are detected by the machine learning model deployed on Raspberry Pi, the weeder will not stop. Suppose the image captured is identified as a weed. In that case, the Raspberry Pi will first stop the motor through a PWM signal and activate the relays connected to the pneumatic cylinder and actuator. It will bring the intra-row weeding tool down; after a few seconds of delay, the motor will restart, allowing the weeds to be removed through a forceful dragging action. The intra-row

Table 1: Details of the test soil bin.

Parameters	Values
Plot area	3.35 m*10 m
Inter-row space	300 mm
Intra-row space	150 mm
Number of rows	5
Total number of spring onion crops	100 (per row 20)
Space for crop's spread	300 mm × 300 mm
Total number of weeds	400
Intra-row weeds	100
Inter-row weeds	300

weeding tool will be backed up by actuator and the motor will continue to move. Fig 4 illustrates the workflow of a Weeding Agrobot Prototype.

RESULTS AND DISCUSSION

Results of object detection models

Out of the object detection models tested, YOLOv8n yielded the best results. The model size is tiny, 5.96 MB, making it work properly on the Raspberry Pi. The inference time for the YOLOv8n model is 2 ms. The mAP IoU@0.5 of 0.85 for YOLOv8n (trained for 50 epochs) gave good prediction accuracy. Therefore, this model would be suitable for autonomous weeders to detect weeds accurately. Table (2) shows the model size-wise and mAP-wise comparison of the different tried models.

Different trials of YOLOv8n models are mentioned in Table (3).

The YOLOv8n model was trained for different epochs, yielding better accuracy at 50 epochs. Its performance was tested using both test data and actual data from the onion farm. Fig 5 (a), (b) show the YOLOv8n model's prediction results on test data and the actual field when working in real-time with an autonomous weeder, respectively. Fig 5 (c), (d) Show the normalized confusion matrix for the YOLOv8n model and the precision-recall (PR) curve for the test data, respectively. The mAP@50% threshold was 0.87 and 0.82 for onion and weed detection, respectively.

Performance evaluation of the prototype weeding agrobot

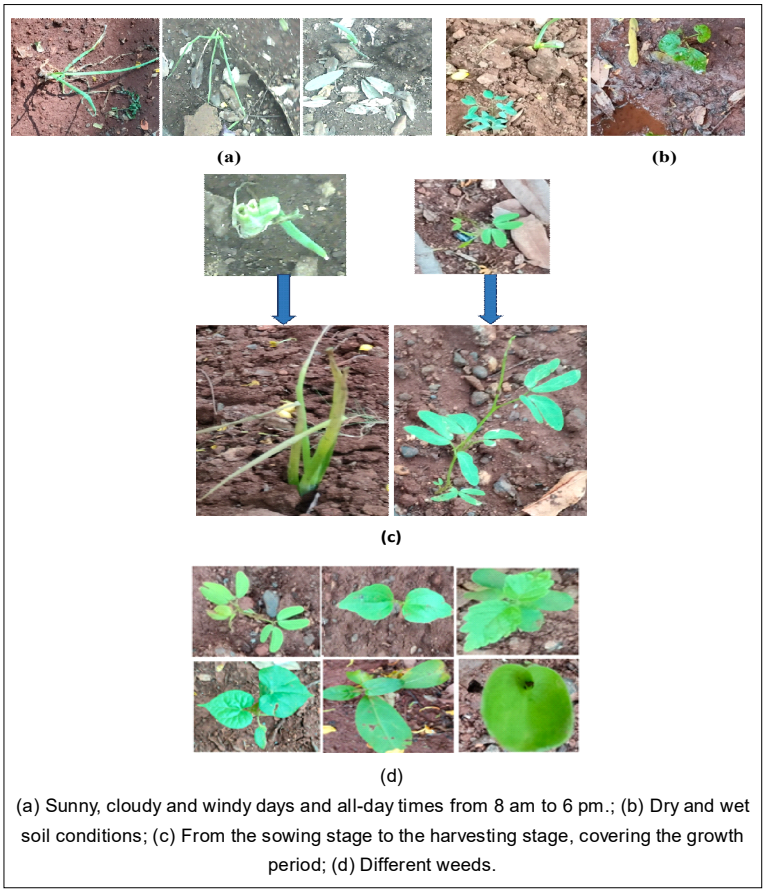
Table 4 shows the parameters of the Weeding Agrobot Prototype and the (Table 5) shows the weeder's average speed, weeding efficiency and plant damage.

Table 2: Comparison of the different object detection models.

Model	Model size (MB)	mAP @ 50% IoU threshold (%)	mAP @ 50-95% IoU threshold (%)
EfficientdetD0	18	6.34	1.87
MobileNetv2 SSD	5.7	42.03	12.89
MobileNetv2 SSD FPN lite	6.5	67.10	30.38
YOLOv8s	21.4	46.4	21.4
YOLOv8n	5.96	85	47.2

Table 3: Trials with YOLOv8n model.

Trial number	Epochs	mAP@50%	mAP@50-95%
1.	100	79.6	35.9
2.	70	81.5	46.6
3.	50	85.0	47.2



(a) Sunny, cloudy and windy days and all-day times from 8 am to 6 pm.; (b) Dry and wet soil conditions; (c) From the sowing stage to the harvesting stage, covering the growth period; (d) Different weeds.

Fig 3: Diverse image dataset.

The weeding operation costs approximately INR 80,000 per hectare of land for the sugarcane crop (Mohan *et al.,* 2020). For the onion crop, this cost increases to INR 12,000. The operation cost of the developed prototype, costing INR 80,000, was calculated by referring to the study presented by author Mohan *et al*. (2020). The hourly fixed cost works out to be INR 46.67. The hourly variable cost, which includes charging costs, repair and maintenance, amounts to INR 11.5. Considering the field capacity, the hourly operation cost per hectare would be INR 2,529. That means the prototype significantly reduces weeding operation costs by 80% compared to traditional methods.

Table 4: Parameters of the prototype autonomous weeder.

Parameters	Values
Width of cut (mm)	600
Depth of cut (mm)	30
Average speed (m/s)	0.12
Theoretical field capacity (ha hr^{-1})	0.026
Effective field capacity (ha hr^{-1})	0.023
Field efficiency (%)	88.45
Specific soil resistance (N cm^{-2})	3.924
Draft force (N)	706.32
Velocity (m s^{-1})	0.12
Power input (hp)	0.11
Performance index (ha hp^{-1})	1726.26

Experimentation

PWM was set at different values and the performance index for every setting was calculated. At 40% duty cycle, the best results were achieved (Table 6). The intra-row space was varied and the intra-row weeding efficiency was evaluated. For a very small intra-row distance, the machine learning model did not perform well; therefore, various experiments were conducted to explore different widths of the intra-row spaces. At an intra-row space of 150 mm, the weeder's performance index was the best (Table 7). Table 8 summarizes the models' performances from previous work and compares them with the proposed best-suited YOLOv8n model. As the datasets differ for different crops, directly comparing the proposed model with other previously used models is invalid. The YOLOv8n, nano version model, suitable for real-time applications, gave comparable precision and recall values for the difficult onion-weed detection dataset. Table (9) compares the proposed weeder's different parameters with those of other weeders in the literature. The developed weeder is an autonomous weeder that operates on electric energy, suitable for both inter-row and intra-row operations. In contrast, other weeders either run on fuel or only remove inter-row weeds.

Table 5: Determination of average speed of weeder, average weeding efficiency and plant damage.

Distance travelled (10 m)	Speed (m/s)	Inter-row weeding efficiency WE_{inter}%	Intra-row weeding efficiency WEi_{ntra}%	Superficial plant damage %	Critical plant damage %
Trial 1	0.117	96.36	75	25	3
Trial 2	0.123	93.75	77.27	24	4
Trial 3	0.122	97.78	76.19	26	5
Average	0.12	96	76	25	4
	Average WE%		86%	Plant survival	96%

Each trial covered one row (1 m*10 m = 10 sq. m) and three such trials were taken.

Table 6: Effect of speed on weeder parameters.

Speed (km/hr)	Inter-row weeding efficiency (%)	Intra-row weeding efficiency (%)	Overall weeding efficiency (%)	Plant damage (%)	Actual field capacity (ha/hr)	PI
1.1	80	2	41	6	0.049	674.45
0.85	92	10	51	5	0.04	880.91
0.6	95	30	62.5	5	0.031	1150.39
0.432	96	76	86	4	0.023	1726.26
0.18	75	78	76.5	4	0.01	1468.8

Table 7: Effect of Intra-row spacing on weeder parameters.

Intra-row spacing (mm)	Inter-row weeding efficiency	Intra-row weeding efficiency	Overall weeding efficiency	Plant damage	PI
60	96	60	78	10	1467.82
100	96	66	81	7	1575.08
120	96	74	85	5	1688.41
150	96	76	86	4	1726.26
180	96	76	86	4	1726.26

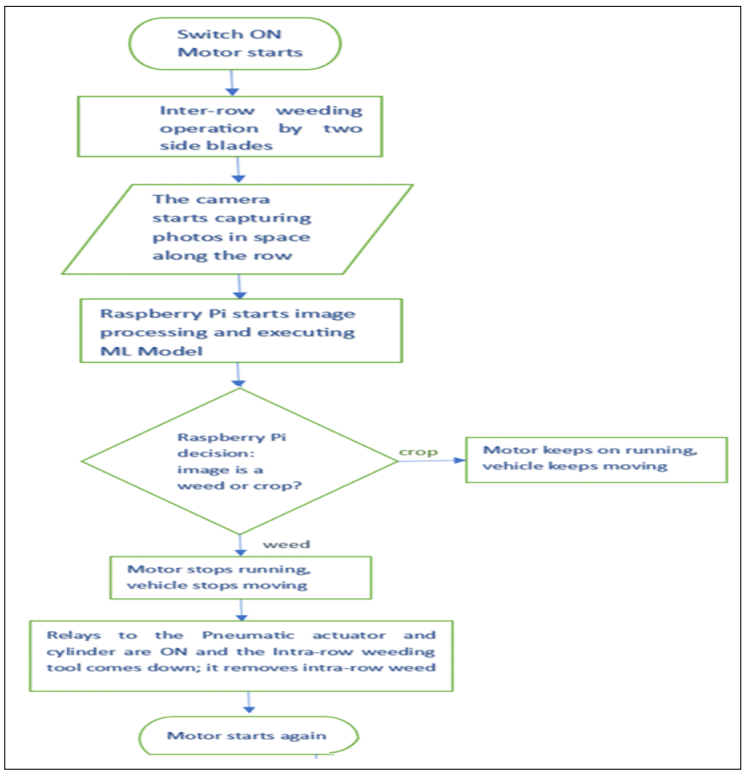


Fig 4: Flow chart of the working.

Table 8: Comparison of performance of the proposed model with previous work.

Model	Ref. paper	Scenario	mAP @ 50% IoU threshold (%)	mAP @ 50-95% IoU threshold (%)	Recall	Precision	Remark
YOLOv8n	Proposed	Spring onion-weed for Autonomous weeder	85	47.2	0.85	0.84	
YOLOv5 SSD-ResNet	Fatima *et al.*, 2023	Sponge gourd, Okra, Bitter gourd; Four types of weeds	88 53	48 25	0.86 N.A.[2]	0.83 N.A.	Heavier model, unsuitable for real-time use.
FCN (fully convolutional network)	Kumar *et al.*, 2024	Classes: Sugar beet, weed, soil	N.A.	N.A.	0.84	0.86	Intra-row spacing: 150-250 mm
YOLOv5n RetinaNet (R101-FPN)	Rahman *et al.*, 2023	Three prominent weed classes in the cotton field	76.58 79.98	55.3 60.2	N.A. N.A.	N.A. N.A.	Nano model; only weeds' classification is done.
YOLOv3	Pandey *et al.*, 2021	Vegetation and weeds	93.81	N.A.	N.A.	N.A.	Dataset from UAV video, heavier model, unsuitable for real-time use.

[2]N.A. = Not available.

Table 9: Comparison of different parameters of the proposed prototype with already existing weeders.

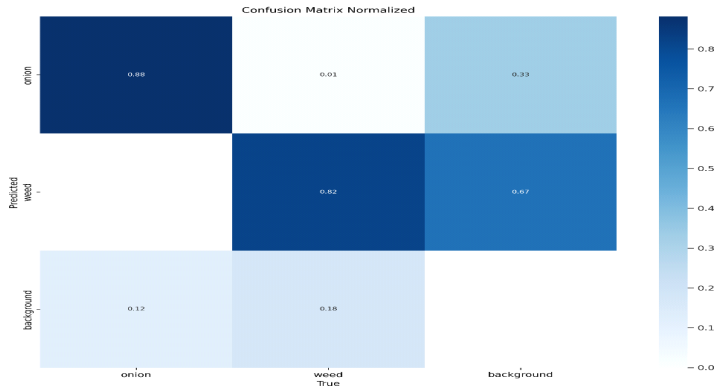
Ref paper	Feature	Speed Km/hr	Power/fuel consumption	Effective field capacity (ha/hr)	Field efficiency (%)	Weeding efficiency (%)	Plant damage (%)	Performance index
Sirmour, Varma 2018	Manually operated rotary-type power weeder	2.45	0.55 l hr^{-1} petrol consumption	0.054	-	88.62		
Sahu, Goel 2017	Multipurpose power weeder for paddy field					84.30		190.81
Singh 2017	Push-pull weeder with a sweep blade	1.25	0.142 hp	0.022		79.72	1	1222.75
Khayer *et al.*, 2024	Self-propelled diesel engine with non-rotary blades	1.48	5.75 hp, runs on diesel engine	0.07	90	94.2	0.01	155.7
Balas *et al.*, 2023	Automated inter and intra-row rotary weeder cum sprayer	1.5		0.153 for brinjal		78.36 for intra-row,85.28 overall weeding efficiency	8.71	197.08
Pandey *et al.*, 2023	E-powered inter-row weeder	3	0.25 hp	0.049		91.68	3.18	
Pandey *et al.*, 2021	Battery-operated power weeder with V-shape blade, straight blade	2-3	0.25, 0.35 hp	0.051, 0.048	90.73,88.50	91.42,86.78	2.37,3.55	2496.30, 1497.04
Proposed weeder	Prototype of an autonomous inter and intra-row weeder	0.432	0.11 hp	0.023	88.46	Inter-row: 96, Intra-row: 76 Overall weeding efficiency: 86	4	1726.26



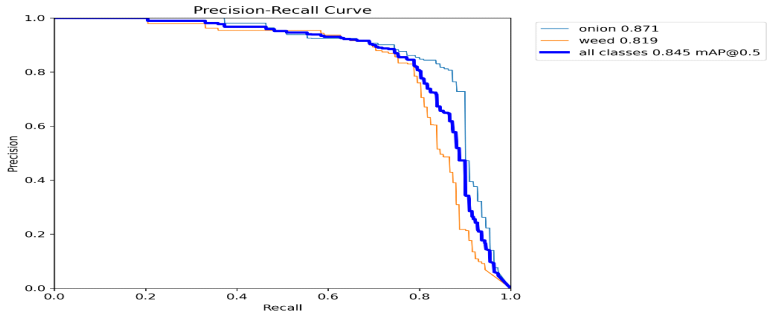
(5a)



(5b)



(5c)



(5d)

(a) Predictions of model YOLOv8n on test data; (b) Predictions of model YOLOv8n on the actual farm; (c) Normalized confusion matrix for YOLOv8n model; (d) PR-curve for YOLOv8n model.

Fig 5: Results of YOLOv8n model.

CONCLUSION

The study concluded that the developed prototype of the Weeding Agrobot for inter and intra-row weeding is compact, easily movable, cost-effective and suitable for small farms in India. To our knowledge, there have been very few previous attempts to classify spring onions and weeds in onion fields. This research contributed a diverse dataset of spring onions and weeds. YOLOv8n was evaluated on the test data and run in real-time by deploying it on a Raspberry Pi, which was used in an Autonomous weeder moving at a speed of 0.12 m/s to cut intra-row weeds within a 150 mm space. The mAP@50% of 0.85 was achieved with an average weeding efficiency of 86% and plant damage of 4%, resulting in a performance index of 1726.26 in real-time applications. Future developments may enable the collection of vast amounts of data, adjustable wheel distances per row, automatic steering, more efficient weeding tools, specialized agricultural tyres and solar-powered batteries. The presented work will guide further work in providing a machine vision to the autonomous weeder and automatically removing weeds. This will help address the labour scarcity problem in agriculture and benefit farmers by enhancing weed management in India.

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Disclaimers

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Conflict of interest

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