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Intelligent intra-row weeding systems using deep learning technology: A review

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Abstract
Huge quantity of herbicide spraying leads to fertile soil deterioration and due to the scope of organic farming concepts, mechanical weeding equipments have emerged as a promising method to eliminate weeds. Inter row weeding is successfully done by cultivators or harrows as they are just dragged behind the vehicles but for intra row weeding, there necessitates intelligent systems. Intelligent intra row weeding system is composed of vision system, control system and intra row weeding device. Identification of crop and weed in field becomes a critical part. Till now, limited varieties of crop and weed are detected by traditional methods due to their distinctive morphological feature but as the complexity increases in external environment and crops and weeds whose morphological feature appear similar creates problem in detection. To overcome such difficulties of detection and identification, intelligent technologies like deep learning concepts are introduced into it. This new technology promises to improve the weeding efficiency in fields. This paper reviews about intelligent intra row weeding systems using deep learning technology.

Keywords: Deep learning, yolo model, weed localisation, intra row weeding, mechanical type, intelligent systems

Introduction

Agriculture production has to be doubled in upcoming days while also protecting the environment and balancing the ecological activities. Weed mitigation in the field plays a prominent role in both these systems. Global yield could reduce upto 34% due to uncontrolled weed growth (Oerke, 2006) [18]. All over the world, in developed countries large farming systems rely on intensive herbicide application methods. This dependence on herbicides can lead to deterioration of soil health, soil pollution, groundwater pollution, decrease in soil organic matter and even cause serious health issues to (MacLaren *et al.*, 2020) [17]. Farmers spend huge amount of money on weed management, often without adequate technical support, resulting in poor weed control and reduced crop yield.

Mechanical weeding is an alternative option for removal of weeds instead of herbicide spraying. It mainly consists of hand weeding, animal drawn cultivators or harrows and tractor drawn equipments. When it comes to annual and biennial weeds, hand weeding or hoeing is a very safe and efficient method. However, human labour is becoming more and more expensive due to the fast industrialization and urbanisation of developing nations (Abouziena *et al.*, 2016) [1]. Animal and tractor drawn equipments remove weeds in inter row region only, once again farmer has to hire labour to remove intra row weeds ending up in a high cost of weeding. In order to remove intra row weeds while also simultaneously removing inter row weeds, there necessitates the inclusion of intelligent technologies.

To enhance the weeding efficiency of inter row weeders, intra row weeding mechanisms are introduced to it. In recent years, many researchers have proposed different types of intra row weeding mechanisms whether detachable or integrated to the mobile platform. Advanced technologies are involved to achieve the goal of intra row weeding mechanism. An intelligent intra row weeding mechanism consists of sensing system, control algorithm and weeding device. Among all, sensing system is most critical part of intra row weeding mechanism as it detects crop or weed. Earlier, crop and weed detection was carried out by ultrasonic, infrared and laser sensors, but there detection capacity decreased when crops and weeds morphology appear same. As the time advanced, machine vision system was developed to precisely identify crop and weed.

Machine vision has enabled automated and robotic weed control to precisely detect and identify the target. It basically consists of dataset acquisition, dataset preparation, digital image processing algorithms. The fact that machine-vision-based systems used for robotic weed management are susceptible to changes in natural light is a concerning issue. This primarily causes problems with feature extraction and vegetation segmentation (weeds and crops versus barren soil, boulders, and residues). Differentiating weeds from crops, which have similar appearances, is another problem. Furthermore, when there is considerable plant blockage, it might be quite difficult to distinguish a single plant (Li *et al*., 2019) [15]. Digital image processing can be done through machine learning or deep learning models. Compared to typical ML approaches, DL algorithms offer numerous advantages for image classification, object detection, and recognition. Crops and weeds often resemble one other, making it challenging to extract and choose differentiating characteristics using machine learning techniques. Thanks to DL methods' robust feature learning capabilities, this problem can be effectively solved. Hasan *et al.,* 2021 [11]. Therefore, DL method is used in intelligent intra row weeding mechanisms to accurately detect and localize the crop and weed position in complex environments. This review paper discusses about intelligent intra row weeding mechanisms involving deep learning technology.

Materials and Methods

Basic principle of intelligent intra row weeding system using deep learning model

When the autonomous vehicle or weeding robot system operates in the field, the camera records real time images of the crop and weed and send them to the portable computer, which processes the images in real time using the computer's deep learning detection model. The control system is not given weeding instructions by the visual detection system when it cannot identify weeds growing between plants and vice versa.

Main components of intelligent intra row weeding system

An intelligent intra row weeding systems consists of three main components which are given below

a) Visual detection and identification of crop/weed
b) Control system
c) Intra row weeding mechanism

Visual detection and identification of crop/weed

Chang *et al.,* 2021 [4] used deep learning model based YOLOv3 network for weed detection and localization. The YOLOv3 tool was a common deep learning model used to quickly detect objects. It was executed in the Darknet environment. Residual neural network (RestNet) and feature pyramid networks (FPN) were its main architectures, which improved the prediction ability of small objects. This network tool was used to detect weed objects. A desktop computer with a high-speed computing processor was paired with a high-speed graphics processing unit (GPU) to train the YOLOv3 network model.

The training model of YOLOv3 was configured as follows: Batch size set to 64, image size resized to 416 × 426 pixels, subdivision of 32, momentum of 0.9, decay of 0.0005, learning rate of 0.001. After that, image preprocessing was performed, including image cropping, white balance, and noise filtering processing, which was then marked by trained technicians and used for model training and evaluation. Among them, 80% of the images were used for training and 20% were used for testing. The bounding box of the region of interest was drawn and exported to YOLO format for model development. Once the weed object was detected, the value "1" was written to the text file. Otherwise, the value "0" was written to the text file. The detection results, including bounding box and labels, were displayed in the image (Fig 1).

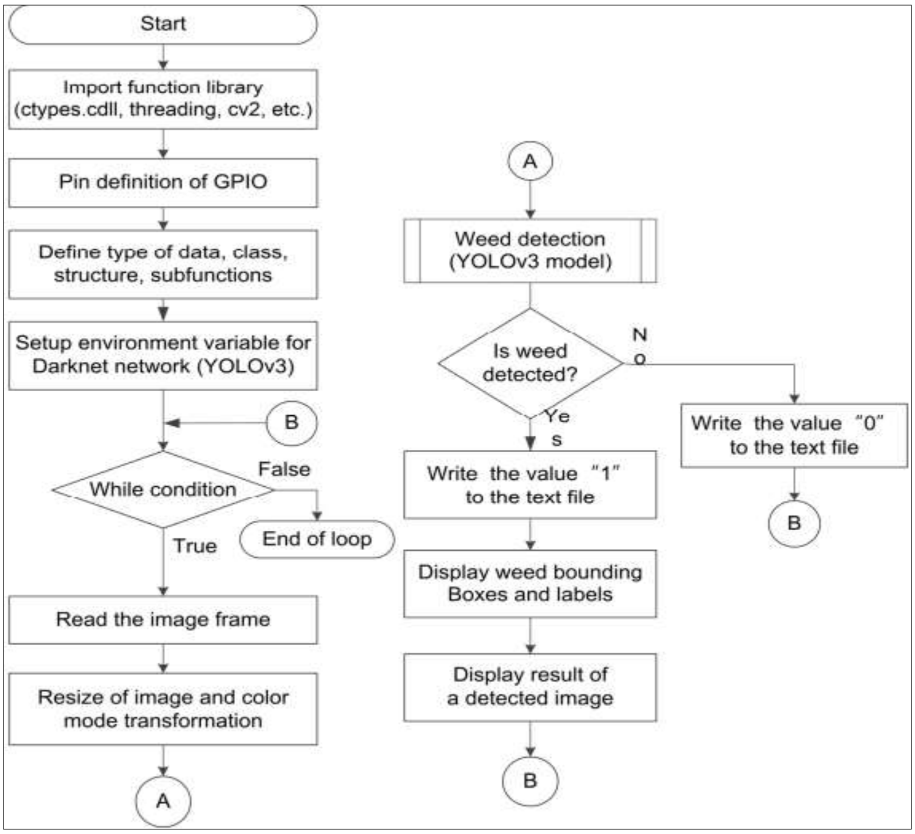

Fig 1: Software program flow for weeding system

Longzhe *et al.*, 2021 [16] used YOLO V4 network model for maize seedling and weed detection. The number of seedling images was eventually increased to 8000 images (Table 1) using the data enhancement method, which included three forms of geometric distortions—flipping, scaling, and translation—as well as four types of photometric distortions—brightness, saturation, noise, and blur. A field seedling data set in PASCAL VOC data set format was created using labelling software; 70% of the data set was utilised for training, and 30% was used for verification. The convolutional neural network's learning capacity is enhanced and computation speed is accelerated by the addition of the CSP (Centre and Scale Prediction) network to the YOLO V4 network model. Fig 2 illustrates how to detect weeds and maize seedlings using YOLO V4. Considering the small size of the weed target, 416 pixels x 416 pixels is the chosen input size, with 0.001 as the initial learning rate and 0.9 as the momentum coefficient, to increase detection accuracy. There are two classes and 20,000 iterations. Out of all the parameters, the training effect is greater when the batch size is set to 7, based on the image characteristics in the data set and the GPU's performance.

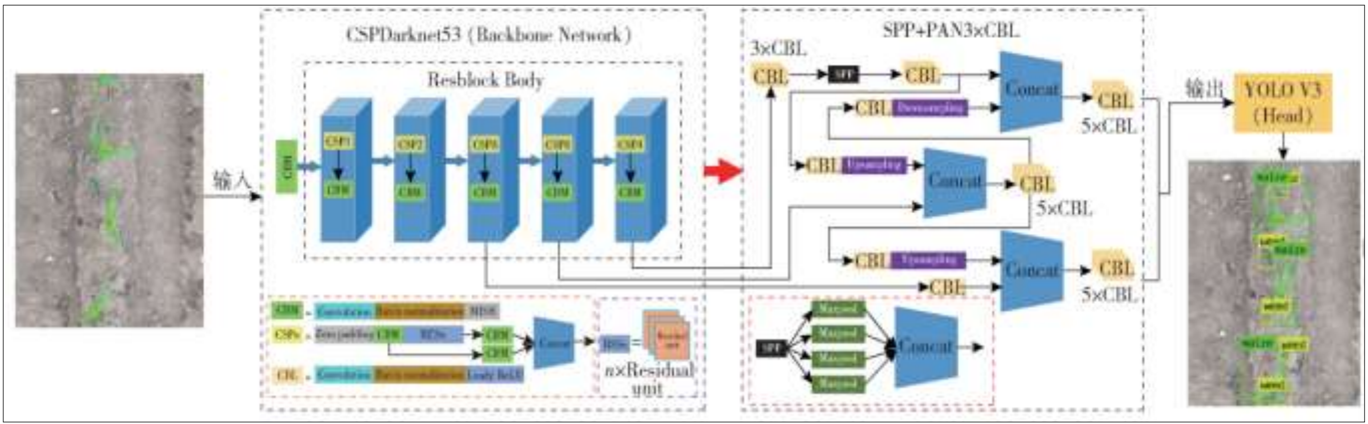

Fig 2: Weeds and maize plants detection based on YOLO V4

Table 1: Number of images generated by data augmentation methods

Data augmentation methods	Raw data	Brightness	Saturation	Noise	Vague	Flip	Zoom	Pan	Total
Image	800	1600	800	1200	1600	800	800	400	8000

Jiang *et al.*, 2023 [12] used SPH-YOLOv5x model for identification and localization of lettuce and weed. Two primary components of the vision system are an industrial camera and a computer. The computer processed the training images after the camera captured them in real time. A maximum resolution of 4500 x 3500 pixels and a frame rate of 30 frames per second are among the camera's specifications. The camera was positioned 500 mm above the ground, with a 50 mm horizontal gap between it and the blade of the weed knife. Each camera has an acquisition range of 400 square centimeters, depending on what the vision system required. The graphics card installed in the machine was an NVIDIA GTX 960. On a server, a workstation including an Intel (R) Xeon (R) Platinum 8156 CPU, an NVIDIA GeForce RTX 3090 GPU, and 20 GB RAM was used for the data training procedure. The following were the training parameters: epoch number 150, batch size of 16, and learning rate of 0.001. A total of 275 original images of lettuce and weed were collected. Data augmentation techniques like flip, rotate, chroma adjustment and brightness adjustment were carried out which enhanced the dataset to 1488 weed images and 430 lettuce images. 372 plant images were used for testing, and 116 plant images were assigned to the training set for the model.

Control system

Chang *et al.*, 2021 [4] A primary control board, relays, DC motors, DC/DC converter modules, proximity switches, and automatic voltage regulators (AVRs) are some of the control circuit components of the weeding system. The motor drive and control decisions, as well as weed detection algorithms, are carried out by the main control unit. Through the Universal Serial Bus (USB) port, the digital camera's photos can be received by the main control board, which will then store them in memory.

The main control board has two sets of relays linked to its general-purpose input/output (GPIO) port. These relays can be used to start and stop the motor by receiving the driving signal produced from the main control board. The square seat in the weeding mechanism is detected using a proximity switch (type: normal open (NO)), and the detection signal is then input into the main control unit via the GPIO interface. Motors and proximity switches, among other circuit components, are powered by the 24 V battery.

The motor control programme is run synchronously while the multi-threaded module is turned on during programme execution (Fig 3). The text file value is opened and read during the while loop. The motor is started by the system when the value is 1, and it is stopped otherwise. To start and stop the motor, a function called Delay is added to the programme along with a delay time.

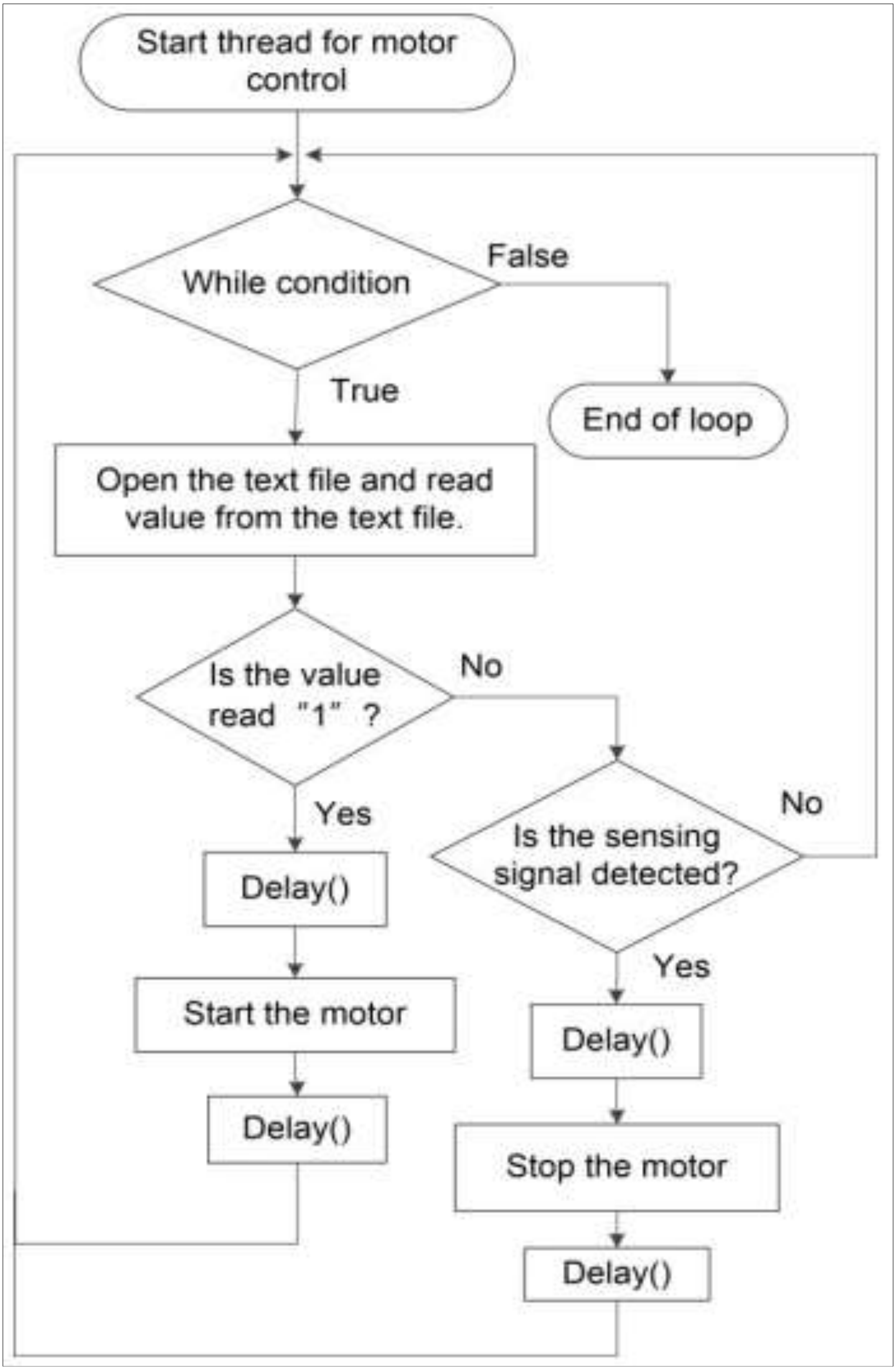

Fig 3: weeding operation program flow

Fig 4 depicts the process of system detection. The mechanical weeding device's servo motor is finally controlled by the control system, which also self-corrects and aggregates the information it has acquired and the stepper motor turns to finish the weeding shovel's vertical ascent towards the lift as well as its horizontal opening and closing. Furthermore, no data is transmitted to the control system in the event that the weeds identified by the optical detection system do not satisfy the weeding requirements (Longzhe *et al.*, 2021) [16].

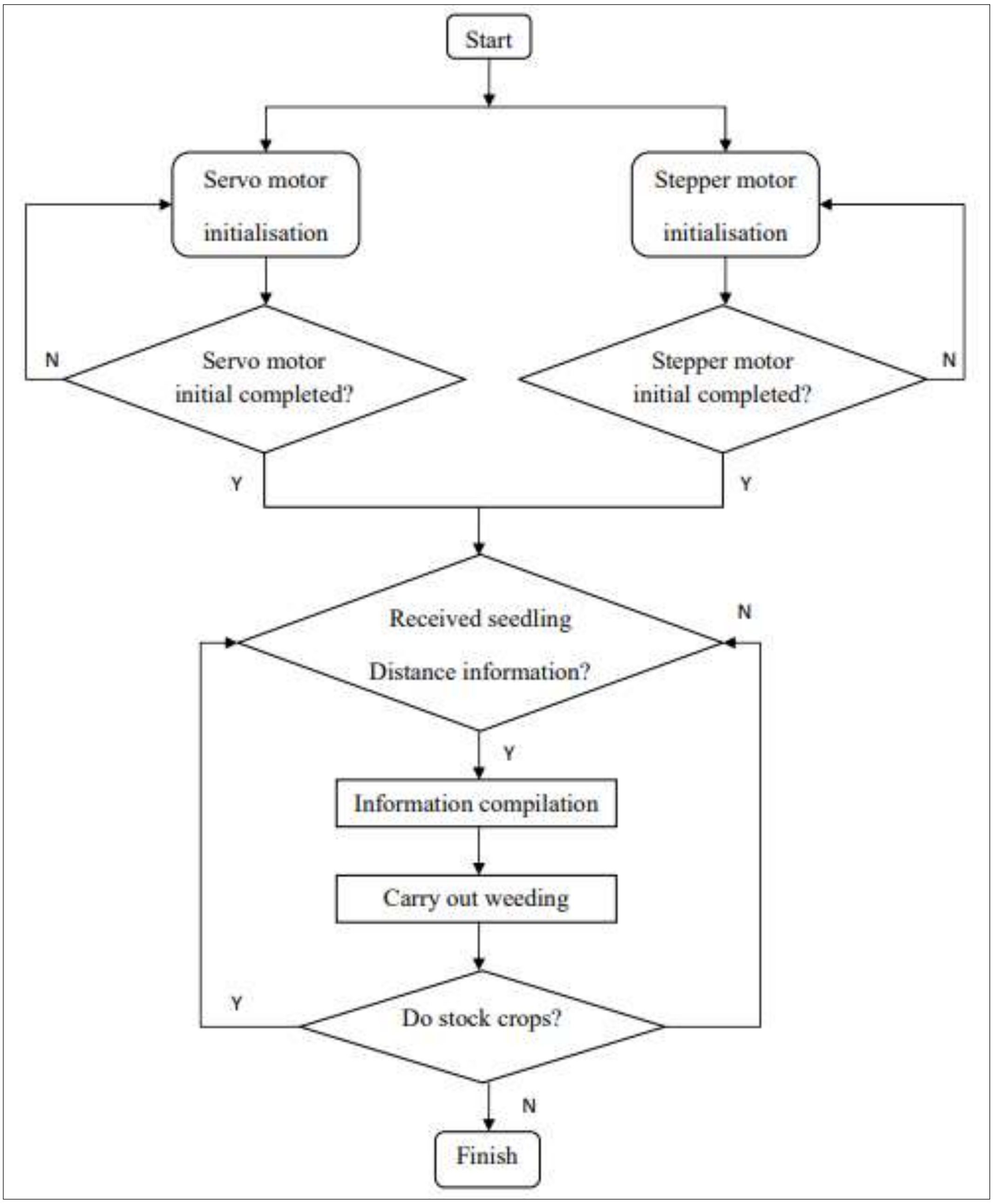

Fig 4: Flow chart of control system

Jiang *et al.*, 2023 [13] created a real-time weed knife control system for intra-row weeding. Fig 5 displays a flow chart for its control algorithm. The conveyor belt on the test platform moves at 3.24 km/h, mimicking the motion of a weed wagon across a field. The camera records video in real time during this procedure and stores it locally on a computer. By obtaining the position of the crop and the tag information, the computer determines where the weed knife is located within the crop. The Arduino microcontroller receives a signal from the computer via the serial port when the weed knife is ready to enter the crop safety zone. At this moment, the weed knife is opened to avoid the crop by means of the Arduino microcontroller controlling the cylinder. It takes hardly no time at all to open the weed knife after the crop is identified.

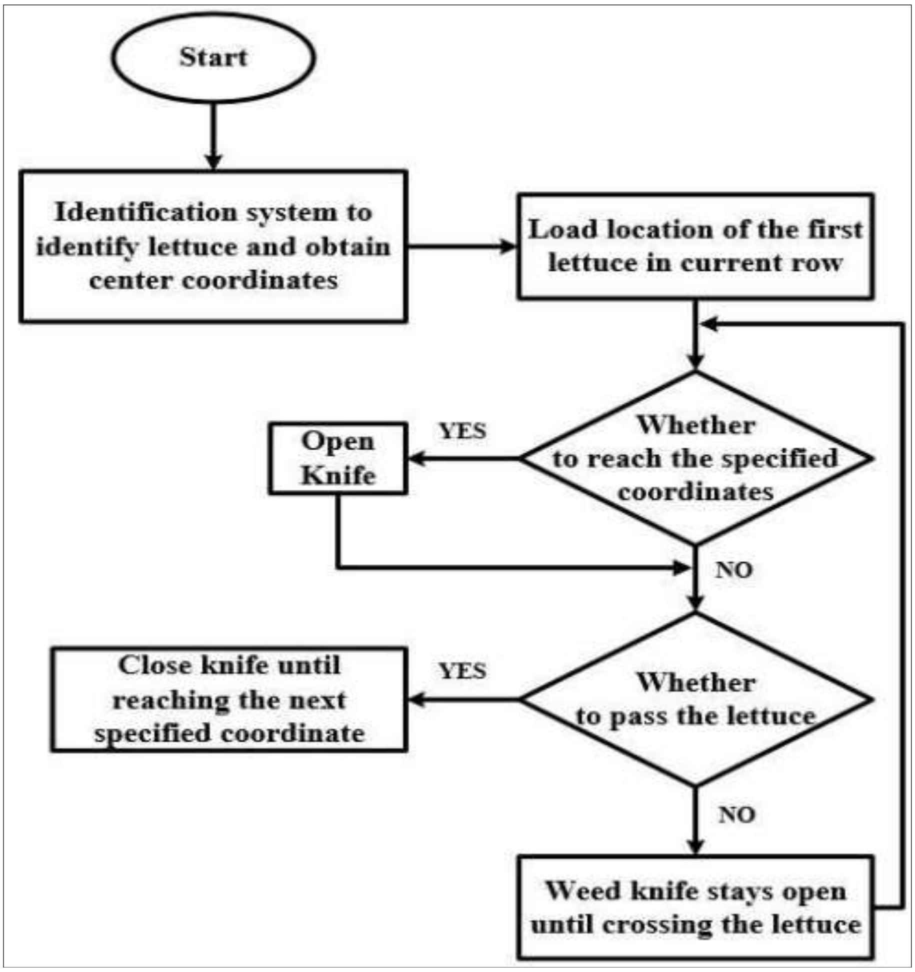

Fig 5: Control program flowchart of the intra-row weeding system

Intra row weeding mechanism

Chang *et al.*, 2021 [4] designed double-gear chain transmission mechanism which exhibits lower transmission loss. This design concept was derived from the mechanical transmission principle of the bicycle. Its components include a DC motor, a transmission mechanism, a height-adjustable weeding handle, and a protective case (Fig 6). The transmission component adopts a sprocket, which is made of medium carbon steel. This kind of tool set is mounted on a rotating mechanism that enables the blade's vertical cutting surface to travel downward by a rotating torsion force in order to shovel soil. A DC motor was used to drive it. When weeds are detected in the intra-row region by the YOLOv3 model, the weeding shovel with a reciprocating swinging behaviour engages when the motor rotates.

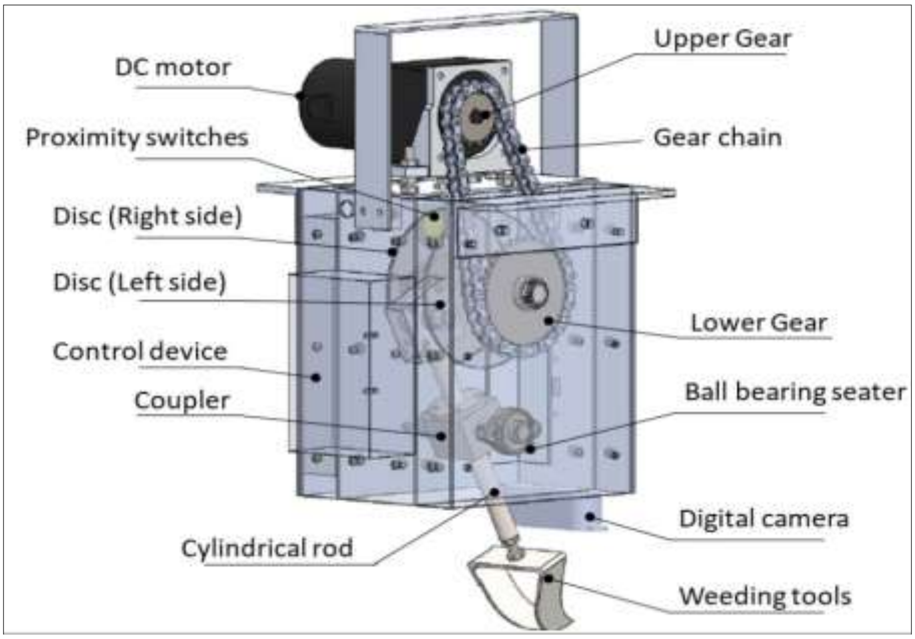

Fig 6: Prototype of weeding mechanism

Longzhe *et al.*, 2021 [16] designed a weeding device based on the three-dimensional movement of weeding shovels, so that the weeding shovel can complete two operation models, including under and on the ground to avoid maize seedlings. The simplified model of this weeding device in corn fields is shown in the Fig 7. The weeding shovel has both horizontal and vertical movement in its three-dimensional spatial movement. The weeding shovel's vertical movement is primarily accomplished by a linear slide module made up of a screw stepper motor, an optical axis, and a slider; a servo motor coupled to a reducer and a right-angle gearbox is responsible for the horizontal opening and closing movements on the left and right. The crank four-bar linkage opens and closes the swing arm after converting the rotational motion around the x-axis into another rotational motion around the x-axis. The swing arm is where the linear slide module is installed. The swing arm is where the linear slide module is installed. The weeding shovel can accomplish three-dimensional opening and closing movement in space when the swing arm and linear slide module function in tandem. This produces the effect of weeding beneath the soil and preventing seedlings from growing on the soil. The weeding shovel is constantly below the ground surface during operation and can only accomplish plane opening and closing movements to reach the soil when it is positioned horizontally during the whole weeding process and is always positioned at the bottom by the linear slide module. The method of weeding that prevents seedlings from growing beneath the soil is the result of doing so.

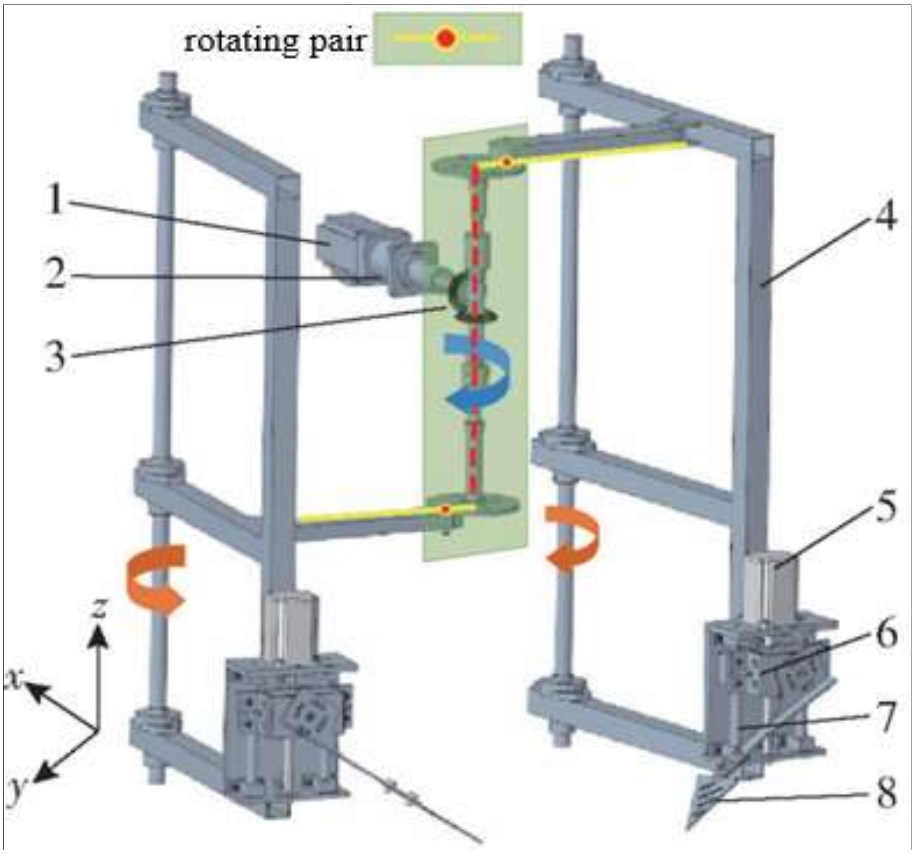

Fig 7: Intra row weeding structure model 1.servo motor 2.reducer Motor 6.slider 7.optical axis 3.Right angle gearbox 4.swing arm 5.Screw stepper 8.weeding shovel

Jiang *et al.*, 2023 [13] The intra-row weeding device's operation is demonstrated in Fig 8. There are three artificially defined regions in the agricultural field: the crop safety area is area C, the intra-row area is area B, and the inter-row area is area A. The weeding knife blade, which is roughly 7 cm wide, was used to manage intra-row weeds within the crop row. The three locations in which the weeding knife blade is moved from left to right are shown in Figure 8b. The weeding blade is positioned in the intra-row area driven by the cylinder in the "closed" position, and both blades advance in parallel. The cylinder divides the blade into the inter-row space along the purple dotted line as it gets closer to the lettuce plant at position 2. The safety zone C remains intact as a result. The cylinder drives the knife blade back into the intra-row space once it has passed the lettuce. With every crop of lettuce, this procedure is repeated. The weeding knife is closed when it is not in the crop area and sinks deeply into the ground. All of the weeds in the area are pulled up by their roots by the conveyor belt as it moves.

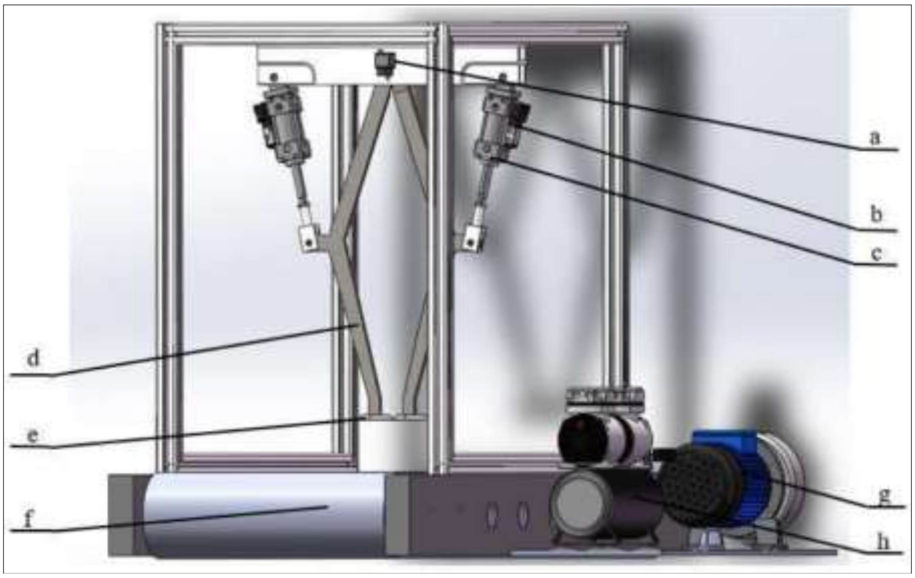

Fig 8: Open-closed intra row weed control device: (a) industrial camera; (b) solenoid valve; (c) pneumatic cylinder; (d) mechanical arm; (e) weed cutting blade; (f) conveyor belt; (g) aircompressor/pneumatic pump;(electric motor).

Table 2: Different studies on YOLO model based crop and weed detection

Sl. No	Reference	Crop	Research title	Dl models applied	Journal name
1.	Chang *et al.*, 2021 [4]	Vegetable crops	Mechanical control with a deep learning method for precise weeding on a farm	YOLOv3	Agriculture
2.	Longzhe *et al.*, 2021 [16]	Maize	Development and Experiment of Intra-row Weeding Robot System Based on Protection of Maize Root System	YOLO V4	Nongye Jixie Xuebao/Transactions of the Chinese Society of Agricultural Machinery
3.	Jiang *et al.*, 2023 [12]	Maize	A SPH-YOLOv5x-Based Automatic System for Intra-Row Weed Control in Lettuce.	YOLOv5	Agronomy
4.	Quan *et al.*, 2022 [21]	Maize	Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode.	YOLOv3	Biosystems Engineering
5.	Dang *et al.*, 2022 [6]	Cotton	YOLO Weeds: A novel benchmark of YOLO object detectors for weed detection in cotton production systems	YOLOv3 , YOLOv4 , Scaled - YOLOv4 , YOLO R an d YOLOv5 , YOLOv6 an d YOLOv7	Computers and Electronics in Agriculture
6.	Ajayi *et al.*, 2023 [3]	Sugarcane, banana trees, spinach, pepper	Performance evaluation of YOLO v5 model for automatic crop and weed classification on UAV images	YOLO v5	Smart Agricultural Technology
7.	Zhang *et al.*, 2022 [25]	Lettuce	SE-YOLOv5x: An optimized model based on transfer learning and visual attention mechanism for identifying and localizing weeds and vegetables	Support vector machines (SVM), YOLOv5x, single-shot multibox detector (SSD), and faster-RCNN, the SE-YOLOv5x	Agronomy
8.	Fatima *et al.*, 2023 [8]	okra, sponge gourd, and bitter gourd	Formation of a lightweight, deep learning-based weed detection system for a commercial autonomous laser weeding robot	YOLOv5	Applied Sciences
9.	Rahman *et al.*, 2023 [22]	Cotton	Performance evaluation of deep learning object detectors for weed detection for cotton☆	YOLOv5, RetinaNet, Efficient Det, Fast RCNN and Faster RCNN	Smart Agricultural Technology
10.	Gallo *et al.*, 2023 [9]	Lincoln Beet Chicory Plant	Deep object detection of crop weeds: Performance of YOLOv7 on a real case dataset from UAV images	YOLOv7	Remote sensing
11.	Osorio *et al.*, 2020 [19]	Lettuce	A Deep Learning Approach for Weed Detection in Lettuce Crops Using Multispectral Images	Tiny YOLOV3	Agri-engineering
12.	Pérez-Porras *et al.*, 2023 [20]	Wheat	Early and on-ground image-based detection of poppy (Papaver rhoeas) in wheat using YOLO architectures.	YOLOv3, Scaled-YOLOv4 (YOLOv4-CSP and YOLOv4-P5 levels), and YOLOv5 (YOLOv5-s, YOLOv5-m, and YOLOv5-l)	Weed science
13.	Chen *et al.*, 2022 [5]	sesame	Weed detection in sesame fields using a YOLO model with an enhanced attention mechanism and feature fusion	YOLOv4 model	Computers and Electronics in Agriculture
14.	Sportelli *et al.*,	turfgrass	Evaluation of YOLO object detectors for weed	YOLO and YOLOv5, YOLOv6,	Applied Sciences

	2023 [23]		detection in different turfgrass scenarios.	YOLOv7, YOLOv8	
15.	Gao *et al.*, 2020 [10]	sugarbeet	Deep convolutional neural networks for image-based Convolvulus sepium detection in sugar beet fields.	Tiny YOLOv3	Plant methods
16.	Ahmad *et al.*, 2021 [2]	Corn and sugarbeet	Performance of deep learning models for classifying and detecting common weeds in corn and soybean production systems.	YOLOv3, VGG16, ResNet50, InceptionV3,	Computers and Electronics in Agriculture
17.	Hussain *et al.*, 2020 [12]	potato	Design and development of a smart variable rate sprayer using deep learning.	YOLOv3-tiny, YOLOv3	Remote Sensing
18.	Dhruw *et al.*, 2023 [7]	Soyabean	Weed Detection in Soybean Crop Using YOLO Algorithm.	ou Only Look Once (YOLO) v3, v4, and v5	Springer
19.	Ying *et al.*, 2021 [24]	Carrot	Weed detection in images of carrot fields based on improved YOLO v4	Improved YOLO v4	International information and engineering technology association
20.	Jin *et al.*, 2022 [14]	Vegetables	A novel deep learning-based method for detection of weeds in vegetables	YOLO-v3, CenterNet and Faster R-CNN	Pest management science

Results and Discussion

The results of weed detection using the YOLOv3 model over various time periods are displayed in Table 3. The findings indicate that the F1 score ranged from 74.3% to 92.8%, with the highest F1-score value occurring between 10:00 and 13:00, when accuracy reached 95.6%. The weeding system has an average weeding efficiency of 88.6% and can detect the weed signal at travel rates of less than 15 cm/s, with a detection speed of 5 fps of YOLOv3. The average detection accuracy rate is 90.7% with an F1-score of 89.5% and a recall rate of 90.1% (Chang *et al.*, 2021) [4].

Table 3: Weed detection with deep learning models in the daytime

Description		**Evaluation metrics**		
Weather	**Time**	**Precision**	**Recall**	**F1-score**
Cloudy and sunny	08:00-09:00	0.902	0.829	0.864
	10:00-11:00	0.956	0.901	0.928
	12:00-13:00	0.936	0.885	0.910
	14:00-15:00	0.918	0.854	0.885
Cloudy	16:00-17:00	0.903	0.833	0.867
	18:00-19:00	0.832	0.701	0.761

The results used YOLO V4 network model for maize seedling and weed detection were shown in Tables 4 and 5. During the test, the robot mobile platform moved at 1.0 and 1.2.1.5 km/h, respectively, across the test field. Three ridges were successfully identified in the images, and statistics were run at each speed. The viability of the seedling and grass visual detection system is confirmed by the corn seedling detection rate, which reaches 96.04% and the weed detection rate, which reaches 92.57%, at a forward speed of 1.2 km/h on the mobile platform. The findings demonstrated that the weeding rates were greater than 81% at a forward speed of 1.2 km/h for the robot mobile platform. The soil-avoiding seedling-avoiding weeding mode has a lower average seedling damage rate and root damage rate than the soil-avoiding seedling-avoiding weeding mode. The average root damage rate has dropped by 36.40 percentage points to 3.35 percent, indicating that the seedlings that avoid the weeding mode on the soil have a good weeding effect (Longzhe *et al.*, 2021) [16].

Table 4: Detection results of maize seedlings

Moving platform (km/h)	**Test serial number**	**Actual number of corn seedlings**	**Detected corn seedlings**	**Average detection rate (%)**
1.0	1	140	135	96.40
	2	135	130	
	3	141	136	
1.2	1	146	140	96.04
	2	143	137	
	3	140	135	
1.5	1	144	129	91.97
	2	150	140	
	3	140	126	

Table 5: Detection results of weeds

Moving platform (km/h)	Test serial number	Actual number of weeds	Detected weeds	Average detection rate (%)
1.0	1	71	62	93.14
	2	124	117	
	3	89	87	
1.2	1	190	166	92.57
	2	82	80	
	3	111	103	
1.5	1	130	101	86.94
	2	99	86	
	3	80	77	

Table 6 displays the analysis of the SPH-YOLOv5x model's classification performance for lettuce crops containing five weeds: *Avena fatua* L. (AF), *Veronica polita* Fries (VP), *Malachium aquaticum* L. (MA), *Plantago asiatica* L. (PA), and *Sonchus wightianus* DC. (SW). In terms of accurately recognising weeds, the model's accuracy rate for lettuce was 92.9%. For PA, the model's classification accuracy was the highest at 98.7%, while for SW, it was the lowest at 89%. Nevertheless, the model maintains a high degree of accuracy in classifying weeds and lettuce. It is clear from looking at the confusion matrix in Fig 9 that the suggested model produces accurate identification and classification results for a variety of weeds as well as lettuce. In the case of light weed density, the weeding knife was effective in removing or burying the weeds, as shown in Fig 10a. Nearly all of the weed roots were effectively removed from the soil by the weeding knife in Fig 10b, which shows moderate weed density. On the other hand, in Fig 10c, weeds were indiscriminately pushed from the front crop to the rear crop by the reciprocating weeding knife, which resulted in an accumulation of weeds around the latter under conditions of high weed density (Jiang *et al.*, 2023) [13].

Table 6: Results of lettuce and weeds classification using YOLO models.

Plant species	Precision (%)	Recall (%)	mAP@$_{0.5\%}$ (%)	F1-score (%)
Lettuce	0.878	0.878	0.929	0.878
VP	0.991	1	0.995	0.967
AF	0.971	1	0.991	0.909
MA	0.888	0.875	0.933	0.876
PA	0.973	0.976	0.987	0.94
SW	0.889	0.85	0.89	0.861

Fig 9: Confusion matrix of the trained SPH-YOLOv5x model

Fig 10: Low, medium and high density weed control effect

Comparison of intelligent intra row weeding systems using deep learning models were represented in Table 7. Highest recognition rate of 95% was achieved by SPH-YOLOv5x compared to 90.7% in YOLOv3 and 92.5% in YOLO V4. Weeding efficiency was high in YOLOv3 about 88.6% compared to 84.76% in YOLO V4 and >80.25% in SPH-YOLOv5x.

Table 7: Comparison of the above discussed deep learning models

Model	Camera resolution (pixels)	Weed control mechanism	Recognition rate (%)	Weeding efficiency (%)
YOLOv3	1920 × 1080	Double-gear chain transmission mechanism	90.7	88.6
YOLO V4	640*480	Four bar linkage mechanism	92.57	84.76
SPH-YOLOv5x	4500*3500	Weeding knife linkage mechanism	95	>80.25

Conclusion

Intra row weeding system need intelligent systems like deep learning technologies to precisely detect and localize crop or weed under occluded and complex environment conditions. Three main components of intelligent intra row weeding system were: visual detection and identification of crop/weed, control system and intra row weeding mechanism. In this study, different deep learning models like YOLOv3, YOLO V4 and SPH-YOLOv5x were trained and tested. Recognition rate of 90.7%, 92.5% and 95% was observed for YOLOv3, YOLO V4 and SPH-YOLOv5x respectively. After getting signals from weed detection system, the control algorithm send feedback signals to weeding mechanism. At last intra row weeds were eliminated by intra row weeding device through specific mechanisms. Fast actuation of weeding tools is possible if deep learning models were adopted. These integrated innovative technologies will enhance the weeding efficiency of inter-intra row weeders and have a huge scope in robotics and automation. Thus it helps in eliminating herbicide spraying from the fields, labour requirements, even reduce the soil pollution and protects the soil biodiversity.

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