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Smart Weed Management and their Profile Mapping using Deep Learning and Digital Mapping

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***Abstract*— Removal of weeds has been a challenging task for farmers. Conventional method of weed removal includes indiscriminate spraying of herbicides despite the fact that the presence of the weed is patchy. To find a better solution for weed management, two prototypes were developed using low-cost hardware and open-source Deep learning models: Prototype-1, used a Raspberry Pi 4 B and YOLO v5 model while Prototype-2, used a more powerful NVIDIA GTX-1080 Ti GPU and YOLO v7 model for weed detection. Both prototypes were evaluated in custom potato fields, targeting common weeds like Chenopodium album and Portulaca oleracea while avoiding potato plants. The prototype-1, due to its low processing capabilities showed a significant lag in real-time detection of weed while the prototype-2 showed promising results with average precision of 97% and recall of 91%. A GPS device and Digital Mapping system was also integrated to calculate the effectiveness of Herbicide after evaluating the before and after results with the help of Smart Agro-Sprayer. These experiments show a promising future for the fusion of latest technologies like AI (Deep learning), Automation, Digital Mapping and Data analytics to solve conventional agriculture problems and promote precision farming to increase crop yield with sustainable model.**

Keywords—Weed detection, Precision farming, Artificial Intelligence, Deep Learning, Digital Mapping

I. INTRODUCTION

Agriculture forms the backbone of global food security and is also an important source of livelihood for billions of people in India which for long has been an agrarian Economy [1]. It also provides sustenance for billions of people worldwide. However, the conventional practices used in farming often fail to address the complex challenges faced by modern agriculture. One of the critical issues plaguing the farming community is the infestation of weeds, which compete with crops for resources such as nutrients, water, light and space, leading to yield losses and decreased profitability. The increased prevalence of several pests primarily affects agriculture in underdeveloped nations. Pests are thought to cause annual output losses in India of up to USD 42.66 million [2]. In order to reduce agricultural losses, more than a thousand chemical and biological pesticides are employed worldwide [3]. Chemical pesticides are widely recognized for their efficacy, however there are concerns regarding their effects on the environment and soil, as well as the residue they leave behind in food products [4].

Farming has traditionally employed manual or automatic spraying of herbicides (hydraulic and hydro-pneumatic sprayers) in a regular, broadcasted manner where herbicides are sprayed evenly throughout the field regardless of uneven or patchy spread of weeds across the field. This practice has high inefficiencies and significant amounts of the active ingredient end up elsewhere in the environment [5] contaminating natural resources [6] [7]. This practice not only harms unintended plants like crops but also raises the level of herbicide consumption, which in turn raises the cost of pesticides for farmers. Applying herbicides indiscriminately also results in losses in agriculture, contamination of soil and water, health issues [8], and also leads to the emergence of new herbicide-resistant weed populations [9]. The solution to this problem is a smart precision system which could effectively recognize the weeds out of crops in real-time and then apply the necessary counter-measures in that localized infested area rather than indiscriminate application. According to Balafoutis et al. (2017) [10], using herbicide just where weeds are present may save expenses, lower the chance of crop damage and excessive chemical residue, and maybe lesser the impact on the environment.

In this paper, a Smart Agro-Sprayer has been developed using technologies such as Computer Vision (Real-time Image + Deep learning), Automation and Digital Mapping to identify weeds in real time in crop fields and spray them with a herbicide using an automatic sprayer. Two different prototypes were developed for the experiment and evaluation utilizing different hardware and software configurations and comparative evaluations were also done on the basis of their performance. This work has been built upon the foundational work of Victor Partel et. al [11] by replacing the previously used object detection model, YOLO v3 with more capable and accurate models, YOLO v5 [12] [13] and v7 [14] and also by using a more powerful embedded GPU, GTX 1080 Ti. Digital mapping and data analytics have also been used to evaluate the effectiveness of the herbicide used on weeds.

II. MATERIALS AND METHODS

The main goal for this paper was to develop a low-cost prototype that could provide the synergy of technologies like computer vision, automation, and digital profiling to help farmers in more efficient weed management. For the prototype development, two different prototypes were developed: Prototype-1 (Figure 1), a relatively low-cost and less powerful prototype that utilizes a Raspberry Pi 4 Model B microcomputer for the necessary computation required for running the CNN (YOLO v5) model in real time with a very low frame rate. Prototype-2, that uses a relatively more powerful GPU to run a more powerful CNN model (YOLO v7) to detect the weed with a higher frame rate input.

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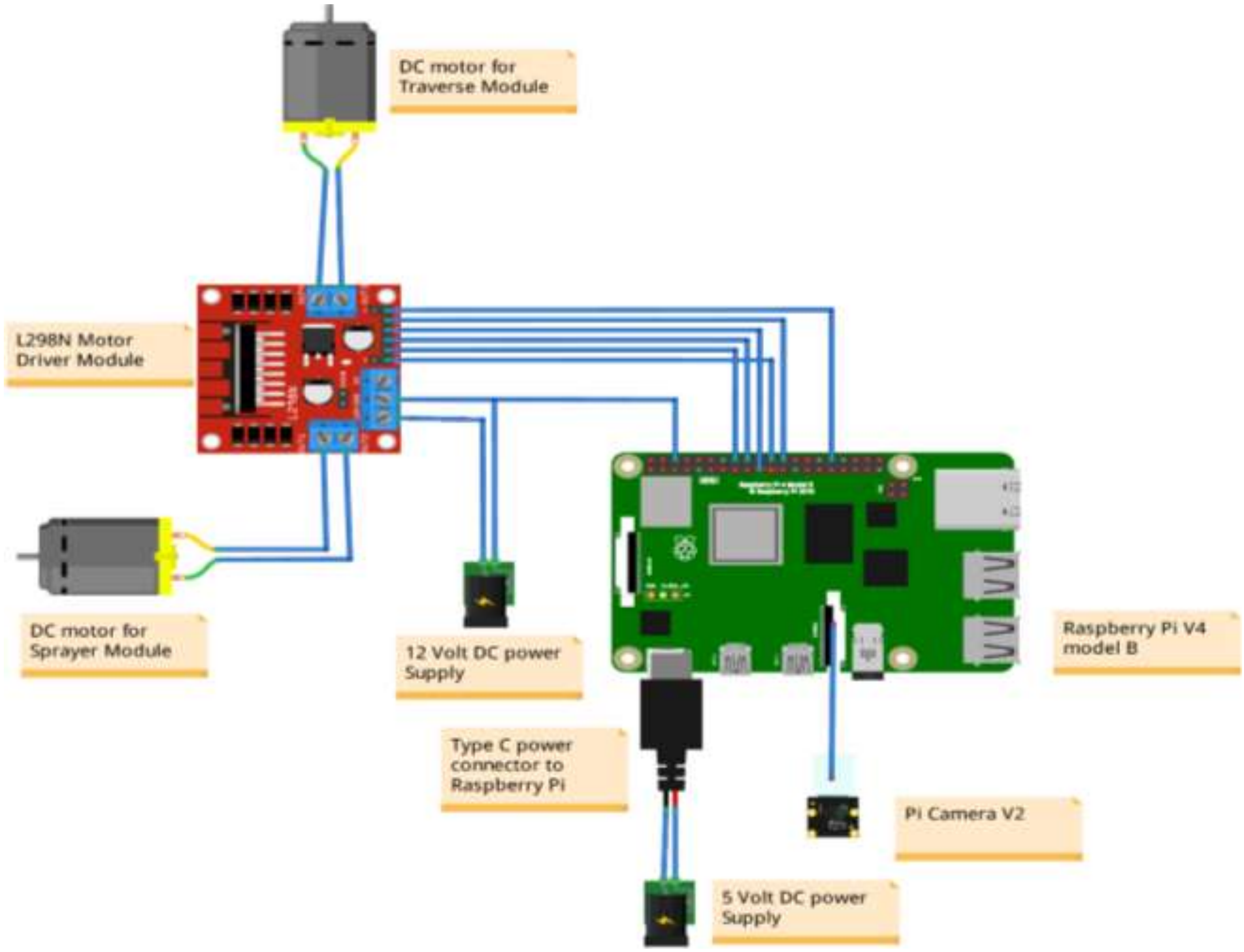

Fig.1. Circuit Diagram for Prototype-1

The first prototype (Figure 1) includes: (i) a Raspberry Pi camera; (ii) a Raspberry Pi 4 Model B.

The second prototype includes: (i) a Logitech C930e camera; and (ii) a microcontroller, Arduino, to manage every sensor and actuator: and (iii) a computational unit (e.g., GeForce GTX 1080 Ti GPU) to support image processing applications like weed detection.

The common materials used in both prototypes include: (i) an individual motor control nozzle; (ii) a pump; (iii) a real-time kinematic GPS kit (precision ~1.5 cm); (iv) the L298 Motor Driver Module and DC Motors for precise control of spraying mechanisms; (v) a 12-volt power supply; and (vi) several relay boards, tubes, pressurized manifolds, etc.

A. Smart Agro-Sprayer Structural Arrangement Description

The sprayer prototype was designed as a modular unit that could be mounted on an ideal traversing platform as per the nature or style of farming so that it could easily travel through the crops. In these experiments, a makeshift ATV or All-Terrain Vehicle which could easily travel between the crop columns was used to mount the smart agro-sprayer system. The camera as well as the spraying nozzle has been mounted on an inverted L shaped non-metallic support with pipe running through it to supply the herbicide. The inverted L shaped non-metallic support was chosen to reduce the weight of mount on the makeshift ATV.

The camera and nozzle were mounted close to each other on the horizontal support with their face vertically down. The distance between camera and nozzle was 4 cm along the horizontal axis. The nozzle was positioned 3 cm lower the camera along the vertical axis to prevent the sprayed herbicide from reaching the camera lens. The camera and nozzle were approximately 40cm above the ground. Now for recording the position of detected weed plants an RTK-GPS device was used with the accuracy of 1.5 cm and an update rate of 3Hz.

Now, coming to the core of this hardware setup: Two different computational units were used where the CNN model as well as the controller program were running. (i) Raspberry Pi 4 Model B; (ii) GeForce GTX 1080 Ti + an Arduino microcontroller.

The Raspberry Pi 4 Model B, an important single- board computer, boasts a quad- core processor and offers RAM options of 1 GB, 2 GB, or 4 GB. It features a standard issue 40- pin GPIO for expansion and requires a 5V DC power supply (minimum 3A). Prices vary, but expect it to be significantly budget than high- end PCs.

The GeForce GTX 1080 Ti is a high- interpretation graphics card that can manage demanding workloads. It makes use of the Pascal architecture, which has 3584 CUDA cores for processing data speedily. With a ultimate boost speed of 1582 MHz, the base clock speed of 1480 MHz guarantees stable interpretation indeed under heavy workloads. It also has a substantial 11 GB of GDDR5X memory, which allows it to manage elaborate graphics and textures. Despite its strength, the GeForce GTX 1080 Ti requires a strong power source to operate at peak effectiveness because it uses 250 Watts of power.

B. Smart sprayer software

To create an application (weed) map and accomplish accurate spraying on the target, software was developed. Figure 2 illustrates the general process flow of the intelligent system. Python was the programming language used in the development of the software. The software operates in real time and can process all phases together at up to 28 frames per second (fps): communication, object detection, and image capture.

1) Image acquisition: At a resolution of 640 × 480 pixels per frame, the software obtains the latest frame from the camera. The photos are then combined side by side to create a single 1920 x 480 pixel image, which is subsequently downsized to a final 1024 x 256 pixel image. This size was determined to be optimal for achieving real-time processing speeds. There is a maximum frame rate of 3 fps for the camera. The GPU's capability and the network being used determine the total processing speed.

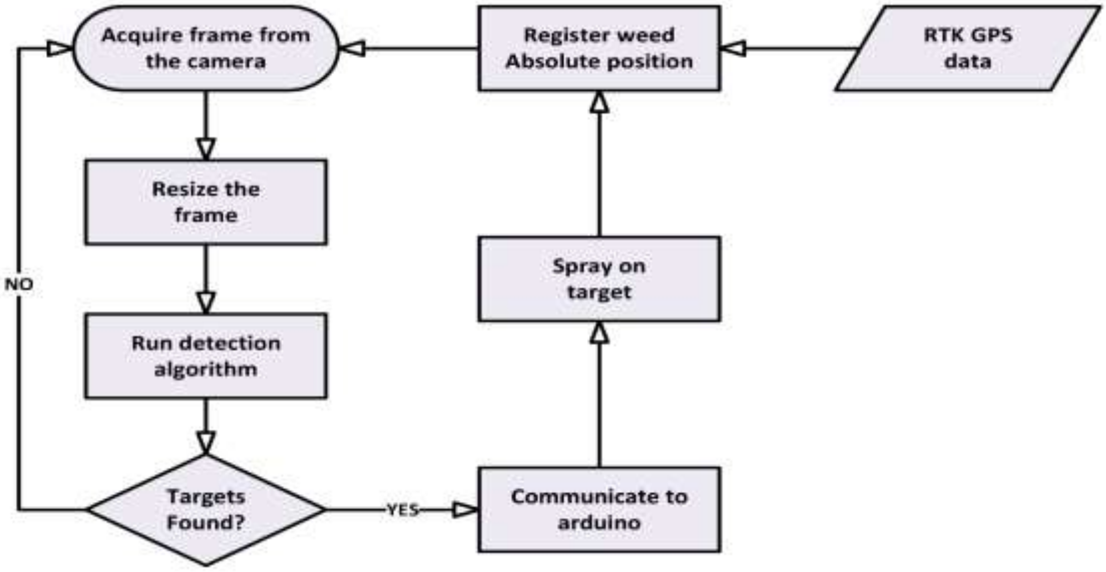

Figure 2: Flowchart for Smart Agro-Sprayer

2) Target detection: Precise target discovery is essential for the smart agro sprayer's effective operation. This exploration delved the deployment of two deep learning models, YOLOv5 and YOLOv7, for weed identification within the agrarian field, using different hardware platforms for optimized performance. Approximately one thousand photos of targets and non-targets with manual labeling for each target position on the images were used to train the network for each trial scenario. and two distinct networks were trained for each test: i) YOLOv5, which features images of crops as non-targets and weeds as targets. ii) YOLOv7, which features images of crops as non-targets and weeds as targets.

The selection of hardware platforms for each network deployment aimed to achieve an optimal balance between performance and resource effectiveness. YOLOv5's deployment on the Raspberry Pi's built- in GPU prioritizes power effectiveness and portability, making it suitable for real-time weed discovery on the edge device during field operation. In discrepancy, YOLOv7's deployment on the GeForce GTX 1080 Ti GPU prioritizes raw processing power, enabling it to handle more complex tasks or potentially handle larger or advanced resolution images.

3) Convolutional neural network and deep learning: Convolutional neural networks (CNN) are used by the YOLO object detection system for object discovery and training. The four primary functions of an introductory CNN are classification, pooling or subsampling, non-linearity, and complexity. Figure 3 shows an illustration of the four primary operations. Based on its visual characteristics, each image can be represented as a three-dimensional matrix of pixel values. The rectangle in Figure 3 illustrates the filter that is applied after the image has been analyzed for features. For a single image, multiple filters may be appropriate. The filter's matrix of values and the matching input picture matrix of values are multiplied. Convolution is the process of multiplying two matrices; thus, the term "convolutional layer." There will be multiple feature maps following the complication layer, one for each filter that was applied. The larger rectangle in the image above represents one region of the image that requires a downsampled image. The next stage involves using the down sampling to construct the feature maps. The stack from the previous set that was produced by down sampling is used to construct a new set of feature maps. additionally, to create a fresh set of feature maps, another down sampling is employed. Afterwards, a fully connected layer that assigns one label to each node at the end is seen. For each image in the training set, this cycle is repeated.

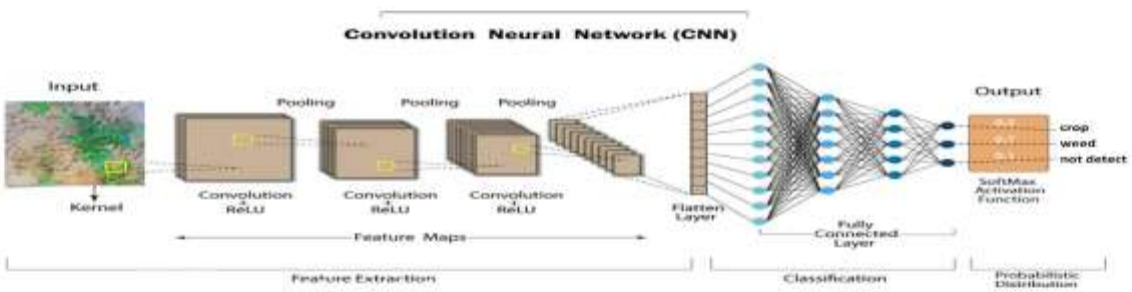

Fig. 3. A convolutional neural network's visual representation.

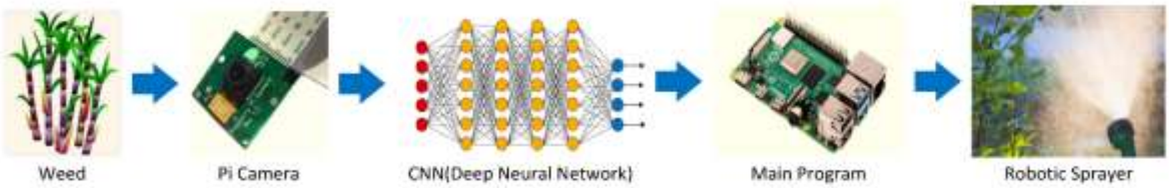

Fig. 4. Schematic diagram of the smart agro-sprayer system

4)

5) Weed Mapping: Using an external RTK GPS device, after every weed detection by the CNN Model. The position of the weed was recorded and saved in a csv file. Later on, the positions were used to generate a digital map using a third party MAP API.

6) Training of YOLO Models: Two different open source, object detection models, YOLO v5 and v7 were trained and employed on the smart agro-sprayer. The training data set consisted of potato and weed pictures sourced from kaggle [15].

III. EXPERIMENT DESIGN

A set of 3 experiments were designed for evaluation of following: i. The accuracy of identification of weed by the computer vision (camera + YOLO model). ii. The comparative performance of the two prototypes. iii. The efficacy of herbicide using grid system.

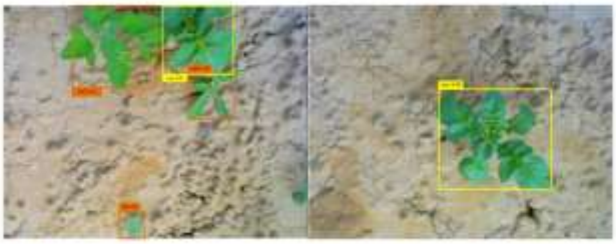

Fig. 5. System detection of target (Weeds) and non-target.

A. Experiment 1: accuracy of prototype-1 (raspberry pi 4 model B + picamera)

In this experiment, the performance of the smart agro-sprayer using a low-cost, single-board micro-computer Raspberry Pi 4 model B (Figure 4) was evaluated in two modes: (i) in a real-time scenario and (ii) in a pre-recorded video with GPS timestamps.

The experimental field was prepared a few months ago with potato plants (Figure 5) as the main vegetable (non-target) and a set of commonly occurring weeds like Chenopodium album (scientific name), commonly known as white goosefoot or Bathua in local north India, and Portulaca oleracea (scientific name), or kulfa in north India which are the target weeds.

The YOLO v5 model was trained such that any plant apart from the crop or vegetable plant would be identified as a weed plant or the target plant, and the sprayer would send a signal to spray herbicide over it. The potato plants were planted in a straight column with an average gap of at least 30 cm, while the weed or any other plant had grown around it.

B. Experiment 2: accuracy of prototype-2 (GTX 1080 Ti GPU + Logitech camera)

In this experiment, the performance of the smart agro-sprayer using a relatively high-cost and more powerful computation unit, an Nvidia GTX 1080 Ti GPU, was evaluated. Unlike experiment 1, here only a real-time scenario was designed for experimentation and evaluation. A new, more powerful and accurate YOLO model (CNN), YOLO v7, was used in this experiment. The arrangement of the field was the same as in the previous experiment. Potato plants were planted in a straight column with an average gap of at least 30 cm, while the weed or any other plant had grown around it.

C. Experiment 3: Weed mapping and herbicide efficiency evaluation using GTX 1080 Ti GPU and RTK GPS system

In this experiment, a portion of the farm was divided into a virtual grid of size 6 x 8 (row x column), where each cell was of dimension 30cm by 30cm. The system was run over each column, and as soon as the system detected any target or non-crop, herbicide was sprayed in that local area, and its position in the grid map was recorded using a GPS-RTK device. The system was run two times, with a gap of a week and a half or 10 days. The results were recorded through the digital grid map for each iteration and this data was later used to calculate the efficacy of the herbicides.

IV. EVALUATION METRICS

After spraying, the smart sprayer's performance was assessed in each experiment by looking at the visual observations made during the process to determine whether areas were sprayed with target or non-target material. The evaluation measures are shown and described in Table 1.

A. Experiment 1: accuracy of prototype-1 (raspberry pi 4 model B + picamera)

By employing the evaluation metrics that have been gathered, the precision and recall of the image recognition system as well as the overall precision sprayer system are determined. The number of true positives over the number of true positives plus the number of false positives is the definition of precision for both systems, whereas the number of true positives over the number of true positives plus the number of false negatives is the definition of recall.

The precision of the detection system tells us how many of the items that were identified as positive (true positives) were actually correct. The precision of the spraying system is represented as:

$$Precision\ of\ the\ system\ = \frac{Case\ A}{Case\ B} \qquad (i)$$

where, A is Total no of plants identified as target and sprayed and N is Total no of targets identified and sprayed.

The Recall of the detection system tells us how many of the actual positive items the system managed to identify. The Recall of the spraying system is represented as:

$$Recall\ of\ the\ system\ = \frac{Case\ A}{M} \qquad (ii)$$

TABLE I: A DESCRIPTION OF THE METRICS USED FOR EVALUATION

Evaluation Metrics		Description
Case A	A target is sprayed	ideal circumstance in which the target was effectively located and sprayed
Case B	A non-target is sprayed	mistaken for a target that wasn't there and sprayed
Case C	Target is not identified	the Image recognition system does not detect the target (weed)
N	total number of targets	The total number of the weeds that are expected to be sprayed
Case X	Initial no of grids with weeds	Initial number of grids marked with weeds in first iteration
Case Y	Total no of grids with weeds in the second iteration	Total number of grids marked with weeds found in the second iteration
Case Y1	Number of old grids with weeds	Number of old grids marked with weeds
Case Y2	Number of new grids with weeds	Number of new grids marked with weeds
P	precision of the system	(Equation-1)
R	recall of the system	(Equation-2)
ST	percentage of sprayed target	Case A/No. of targets (%)
MT	percentage of missed targets	Case C/No. of targets (%)

where, A is Total no of plants identified as target and sprayed and M is Total targets present.

B. Evaluation Metrics Design for Experiment 3.

For the measurement of effectiveness of herbicide, X in experiment 3, following steps were followed:

- Calculate the total number of grids initially marked with weeds : Initial number of grids marked with weeds – X
- Calculate the number of grids with weeds found in the second iteration: Total number of grids with weeds found in the second iteration – Y
- Identify the number of old and new grids with weeds: Number of old grids with weeds - Y1 and Number of new grids with weeds - Y2

The calculation of the effectiveness of the sprayed herbicide are:

$$\text{Effectiveness} = \frac{Case\ X\ - Case\ Y1}{Case\ X} * 100 \qquad (iii)$$

TABLE II. RESULTS FOR THE EXPERIMENT 2, USING THE GTX 1080 TI GPU (ROUNDED OFF DATA)

Reps	Case A	Case B	Case C	P	R	ST	MT
Rep 1	36	2	2	95%	90%	90%	5%
Rep 2	36	1	3	97%	90%	90%	7%
Rep 3	34	2	4	94%	85%	85%	10%
Rep 4	39	0	1	100%	97%	97%	2%
Rep 5	38	1	1	97%	95%	95%	2%
Average				**97%**	**91%**	**91%**	**5%**

V. RESULT

A. Experiment 1: accuracy of prototype-1 (raspberry pi 4 model B + picamera)

The result of experiment-1 demonstrated that micro-computers like the Raspberry Pi are not capable enough to perform real-time image processing.

The prototype-1 with Raspberry Pi 4 B and YOLO V5 model was evaluated in two modes, first in real time in very low frame rate, the system showed very significant lag and the results were too poor for any practical application, and in second mode, a pre-recorded video of the field was used where raspberry pi was able to run the YOLO model and gave a promising result of around 60% accuracy.

B. Experiment 2: accuracy of prototype-2 (GTX 1080 Ti GPU + Logitech camera)

In this experiment, the performance of the smart agro-system integrated with GTX 1080 Ti and CNN model YOLO v7 was found very promising. The result of precision and recall of a set of 5 repetitive experiments have been shown in Table 2. The average precision and recall of the system were 97% and 91% respectively. The total no of targets (weed), N used in the experiment was 40.

C. Experiment 3: Weed mapping and herbicide efficiency evaluation using GTX 1080 Ti GPU and RTK GPS system

In this experiment the result of effectiveness of herbicide, X on weeds was following:

In iteration 1 (Figure 6(a))

- Initial number of grids marked with weeds (X) = 12

In iteration 2 (Figure 6(b))

- Total number of grids with weeds found in the second iteration (Y) = 6
- Number of new grids with weeds (Y2) = 2
- Number of old grids with weeds = 6 - 2 = 4

Here, in Figure 6(a) and Figure 6(b), X shows where weeds are found.

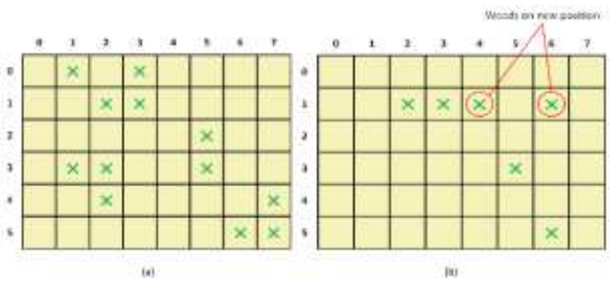

Fig. 6. (a) 1st Iteration (b)2nd Iteration (after one week or 10 days)

The effectiveness of the sprayed herbicide is calculated by using (Equation-3):

$$\text{Effectiveness} = \frac{12 - 4}{12} * 100$$

$$\text{Effectiveness} = 66.67\%$$

VI. CONCLUSION

Two prototypes were developed for automatic weed detection and spraying utilizing technologies like AI (CNN) and Automation. The prototype-1 used a low-cost Raspberry pi 4 model B micro-computer along with a light CNN model, YOLO v5 and the 2nd prototype used a relatively more powerful and costly GPU GTX 1080 Ti and more latest YOLO model v7. Prototype-1 was found not suitable for practical application due to its hardware limitations. Prototype-2 showed very promising results in detecting and spraying weeds with a precision of almost 97%. An RTK GPS device was used to track weeds before and after spraying of a particular type of herbicide to measure the effectiveness of herbicide. The effectiveness as per the used evaluation metrics was found to be 66.67%.

VII. FUTURE RESEARCH

The CNN model will be trained on more diverse crops and weeds. A new model will be trained such that it could even identify the species of weed and with the help of AI could suggest more effective herbicide for his/her different crop fields. The farmer will have more insight into his field like which field and crop are more prone to which type of weeds etc.

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