

An IoT Based Real Time System for Weed Identification and Selective Removal in Mixed Farming Environment

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Abstract: *This project promotes sustainable agriculture through the creation of an autonomous rover for weed detection and removal with deep learning as the engine. The system combines high-speed object detection models from the YOLO (You Only Look Once) family. It can detect objects with up to 89.4% accuracy (YOLOv5) and process images in 0.6 seconds (YOLOv5). The model uses computer vision to solve the "green-on-green" problem by telling weeds apart from crops based on their shape, texture, and colour. The rover uses built-in processors like the Raspberry Pi and Jetson Nano, as well as motor drivers and proximity sensors, to move around and manage power efficiently. The system makes it possible to apply herbicides or remove weeds mechanically with great accuracy, cutting down on manual labour by about 80%, this cost-effective and scalable method shows how powerful intelligent automation can be in farming, encouraging better weed control and higher crop yields.*

Keywords: Weed Detection, YOLOv5, autonomous rover, Deep Learning, Precision Agriculture, Sustainable Farming

I. INTRODUCTION

A crucial component of contemporary agriculture, weed control has a direct impact on crop yield, quality, as well as general sustainability. Traditional techniques like chemical herbicide application and manual weeding are frequently time-consuming, labour-intensive, and harmful to the environment. Intelligent and automated weed control solutions are becoming more and more necessary as sustainable farming methods gain popularity. Recent developments in deep learning and computer vision have made it possible to create autonomous systems that can precisely identify and remove weeds. This project develops an autonomous rover that can identify weeds in real time using a Raspberry Pi processor and a high-definition camera. The system efficiently separates crops from weeds using visual characteristics like colour, shape, and texture by utilizing image processing and YOLOv5-based deep learning techniques. This automation lowers reliance on pesticides, increases overall farm productivity, and uses less human labour. A major step toward precision agriculture is the combination of deep learning algorithms and hardware, which makes scalable, environmentally responsible, and sustainable weed control techniques possible.

II. LITERATURE SURVEY

A. Drawbacks of Conventional Approaches:

In the past, there were two main strategies used for weed control:

- Manual Removal: Time-consuming and labour-intensive, this method is not feasible for large-scale farming operations [2].
- Chemical Herbicides: Despite their effectiveness, these techniques raise production costs, pollute the environment, and encourage weed species that are resistant to herbicides [3]. The necessity for precision-based alternatives is further highlighted by the non-selective nature of traditional spraying [4].



B. Transition to Systems Based on Vision:

Robotics and computer vision research for site- specific weed management was spurred by the inefficiencies of conventional methods.

- **Early Machine Vision:** Initially, traditional image processing methods like thresholding, edge detection, and colour-based segmentation—in conjunction with conventional machine learning models such as Random Forests and Support Vector Machines (SVMs) [5, 6]. These techniques, however, had poor generalization and were highly sensitive to changing backgrounds and lighting.
- **Transition to Deep Learning (DL):** Convolutional neural networks (CNNs) have made it possible to extract hierarchical features automatically, which has improved accuracy and robustness in distinguishing weeds from crops, particularly in the "green-on-green" challenge [7], [8].

C. Real-Time Architectures' Emergence:

Research turned to real-time object detection models that could be used in the field as computing power increased.

- **YOLO Algorithms:** The speed and accuracy of the You Only Look Once (YOLO) family of single-stage detectors helped them become well-known [9]. Later versions, such as YOLO8 and YOLOv9 incorporated Attention mechanisms and enhanced feature pyramids to improve the detection under occlusion and for small weed targets [10].
- **Model Integration:** Hybrid architectures combining DenseNet-121 for classification and YOLOv5 for real-time localization showed better detection reliability [11]. Non-Deep learning systems some low cost implementations still employ traditional colour Indices and morphological analysis for segmentation and navigation tasks

D. Implementation and Future Trajectory:

Recent research also highlights integration of hardware and software for practical deployment.

- **Robotic Platforms:** There are studies documenting the use of Raspberry Pi and NVIDIA Jetson boards as embedded processing units for autonomous agricultural robots [13].
- **Navigation:** Approaches range from GPS Path following based on vision-guided navigation using crop-row vanishing point estimation [14].
- **Targeted Actuation:** Modern systems employ precision actuators, such as micro sprayers or mechanical cutters-for weed removal, under feedback control algorithms that protect nearby crops [15]. These studies together highlight the Technological development toward autonomous, vision-based weed detection systems. While high-end deep learning models provide excellent accuracy, they require heavy computational resources. In contrast, Raspberry Pi-based implementations offer a balanced, low-cost, and scalable alternative. This project builds upon these foundations by integrating YOLOv5 combined with the autonomous rover platform is able to achieve efficient and sustainable weed detection in real-time agricultural environment

III. PROPOSED SYSTEM

The proposed system includes an autonomous rover designed for weed detection and removal in agricultural fields. It integrates both hardware and software components to identify weeds using image processing and deep learning techniques. The rover navigates autonomously through the field and takes pictures, classifying them in real time and triggers weed removal actions. The central hardware modules of the system components include a Raspberry Pi, camera, motor drivers, chassis, battery and communication module

A. Raspberry-Pi: The Raspberry Pi is the central processing unit of the rover in charge of carrying out image processing and control algorithms. It processes images captured by the camera, detects weeds using the trained YOLOv5 model, and issues navigation and actuation commands. Its Linux-based operating machine running flexibility provided in this system learning inferences in real time.

B. Camera: A high-definition camera is mounted on the rover to take continuous images of the field as it moves. The camera provides clear, high-resolution visuals even under variable lighting conditions to assure consistent weed



identification. These images are analyzed by the Raspberry Pi using pre-trained deep learning models to detect and classify weeds.

C. Motor Drivers: The rover's mobility is powered by two DC motors controlled by an L298N motor driver. The Raspberry Pi sends PWM signals to the driver, which controls the speed and direction of movement. The navigation algorithm determines the path that the rover will follow in its motion ensure full field coverage while avoiding obstacles.

D. Rover Chassis: The mechanical framework of the rover is designed for stability and portability, it houses the motors, camera, Raspberry Pi, and battery providing a sturdy structure able to crossing over irregular and soft farming grounds.

E. Battery: A rechargeable lithium-ion battery powers the entire system, including the Raspberry Pi, camera and motors. The power system is optimized for prolonged field operation ensuring autonomy recharging.

F. Wi-Fi Modul: Without frequent Wi-Fi communication module allows for remote monitoring and controlling the rover using a mobile system or laptop interfaces. This feature allows users to change operational parameters such as navigation speed or detection sensitivity and to receive real-time performance feedback during operation, the rover travels across the field along a predefined path continuously capturing image processing and analysis. YOLOv5 model running on the Raspberry Pi identifies weeds in each frame to distinguish them from crops. While navigation is guided by detection results, actuation commands, enable efficient, collision-free motion and accurate weed removal.

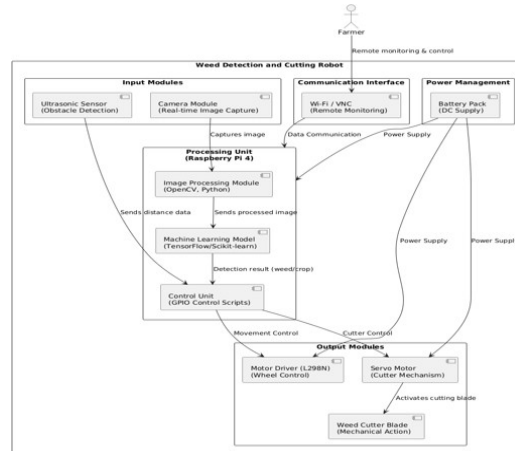


Fig. 1: Flowchart of the weed detection process

The core process is a seamless loop of detection and action:

1. Continuous Scanning: During this process, the rover navigates along a very precise, pre-set path across the field and continuously captures images of the ground.
2. Real-Time Classification: YOLOv5, which runs directly on the powerful Raspberry Pi, takes those images and instantly identifies any weeds from crops, based on learned features such as colour, texture, and leaf shape.
3. Targeted Removal: Once a weed has been identified, the position of the weed is instantly calculated, and the corresponding actuator—a micro-sprayer or mechanical cutter—is triggered to effect precise removal, while protecting the neighbouring crop.

This integrated approach of autonomous movement, machine vision, and deep learning significantly reduces both manual labour and destructive broad-spectrum herbicides, thus making the farming highly efficient and environmentally sound.



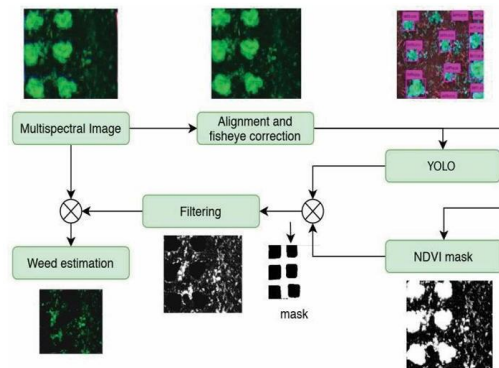


Fig. 2. Flow Diagram for model working System

IV. METHODOLOGY

The system will use deep learning for real-time weed detection and removal with the YOLOv5 architecture. In this regard, the model is trained on images of crops and weeds taken under different light and environmental conditions and labelled accordingly. Later, this model will process video frames from a camera installed on the rover, identify the position of weeds in real time, and draw bounding boxes around them. These detections are streamed with their corresponding coordinates in to the control module, which steers the rover towards the weed and triggers a mechanical cutter to remove it. This strategy minimizes herbicide application and crop damage, ensuring precise autonomous weed control across variable field scenarios.

A. Data preprocessing:

In particular, the training dataset of the YOLOv5 model was a labelled image dataset from crops and weeds taken from different conditions in the field, such as varying light conditions, soil backgrounds, and stages of growth. All these images were annotated using the labelling tool to identify the bounding box of the weed regions. In order to improve model generalization and avoid overfitting, various data augmentation techniques were performed, such as random rotations, random horizontal flips, adjustment to brightness and contrast, and scaling. Images were resized uniformly to 640×640 pixels with normalization to keep all pixel intensities consistent. This work adopted a division of 70% for training, 15% for validation, and 15% for testing to systematically evaluate the performance. Transfer learning of pre-trained YOLOv5 weights on COCO datasets allowed for faster convergence and improved accuracy despite the limited agricultural data.

B. Data classification:

Weed detection and classification in the proposed system are performed using a YOLOv5 deep learning model. YOLOv5 carries out both feature extraction and classification using its convolutional layers, eliminating the need for explicit feature engineering. The model automatically learns to identify weeds from crops by detecting distinctive appearance features that involve leaf shape, colour, texture, and spatial pattern. During training, the given image undergoes multiple convolutional and pooling layers in succession, extracting useful patterns automatically. A final detection head assigns class probabilities to each bounding box, classifying it as "weed" or "crop." This integrated approach to classification has made accurate real-time predictions of the system possible in complicated field environments with variable lighting and background conditions.

C. Building a deep learning model:

The proposed deep learning model for increasingly autonomous weed detection is developed using the YOLOv5 architecture, a single-stage object detection framework known for its real time performance and high accuracy. The model performs feature extraction and classification within an integrated network, this eliminates the need for manual



feature engineering. The model was trained using the annotated dataset prepared in the pre-processing stage. Training was done with a batch size of 16, learning rate of 0.001, and 100 epochs using the Adam optimizer. The loss function is combined bounding box regression, objectness and classification loss to ensure balanced optimization. Transfer learning on pretrained YOLOv5 weights (trained on the coco dataset) was used to accelerate convergence and improve accuracy with limited agricultural data. The YOLOv5 architecture comprises three key components- backbone, neck, and detection head—which together perform feature extraction, multi-scale fusion, and object prediction. The backbone, based on CSPDarknet53 extracts high-level visual features such as leaf shape, colour, and texture. The neck implemented using a Path Aggregation Network (PANet), enhances feature fusion across multiple scales to detect weeds of various sizes and orientations. Finally, the detection head predicts bounding boxes, objectness scores, and class probabilities for "weed" and "crop."

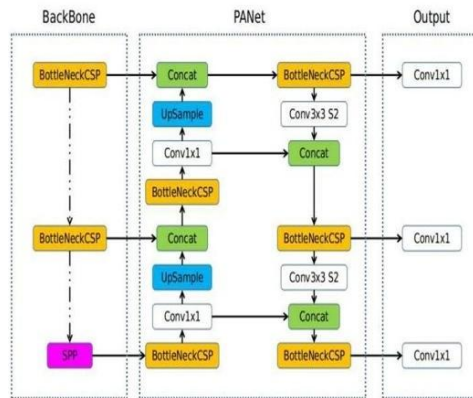


Figure 3 : YOLOv5 Architecture

In the YOLOv5 pipeline, the resized 640×640 - pixel input images go through a sequence of convolutional layers followed by residual blocks. These help to avoid the vanishing- gradient problem, improve convergence rates, and enhance generalization, allowing much deeper features to be learned in the network. This approach aids in detecting objects of various shapes by making predictions based on pre-defined anchor boxes of different scales and aspect ratios. The network suppresses the overlapping detections using NMS and keeps only the most confident ones. The result output consists of labelled bounding boxes with confidence scores as shown in Figure 4.



Figure 4 : Super resolution for weed detection

To further improve image quality and detection precision, a super-resolution module based on a convolutional neural network is integrated before detection. The process reconstructs high- resolution images from low resolution inputs, revealing finer weed features and improving mean Average Precision (mAP) values by reducing false positives. The model was trained on an annotated dataset prepared during preprocessing using the labelling tool. Data augmentation techniques such as random rotation, horizontal flipping, scaling, and brightness adjustments were applied to enhance robustness in different lighting and soil conditions. Training was done in batches of size 16, learning rate of 0.001, and 100 epochs, using Adam optimizer, the loss function combined bounding-box regression loss, objectiveness loss, and classification loss to achieve balanced optimization. Transfer learning was employed using pre trained YOLOv5 weights on the Kaggle dataset enables faster convergence and Improved performance with limited agricultural data. The training process was monitored using metrics like Precision, Recall, F1-score, and mean Average Precision (mAP@0.5). Early stopping was used to avoid overfitting and ensure generalization to unseen field conditions.



The final trained model it achieved an mAP@0.5 of 0.82, precision of and mean Average Precision (mAP@0.5). Early stopping was applied to prevent overfitting and ensure generalization to unseen field conditions. The final trained model achieved an mAP@0.5 of 0.82, a precision of 0.84 and a recall of 0.87, thus showing strong real-time detection capability suitable for deployment on embedded systems like the Raspberry Pi 4. The overall workflow used for weed detection and removal is shown in Figure 6. The trained YOLOv5 model continuously processes video frames from the rover-mounted camera to detect weed locations. Upon detecting the rover's control system computes the target position and orientation using a Proportional Integral-Derivative (PID) feedback controller. The rover then orients itself toward the detected Weed and actuates the mechanical cutter for precise removal. Model performance can be further optimized by the additional dataset hyperparameter tuning for higher detection accuracy.

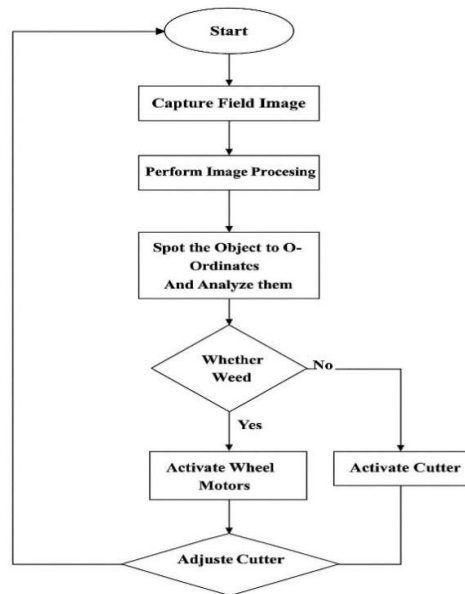


Figure 5 : Flowchart for weed detection and removal

D. Training the model:

The model used, YOLOv5, was trained using the annotated dataset prepared during the preprocessing stage. Training was performed on Google Colab with an NVIDIA Tesla T4 GPU to ensure high-speed computation. The dataset consisted of images labelled as weed or crop, allowing the model to learn distinguishing visual patterns. Each image was resized to 640×640 pixels and Normalized before being fed into the network. Data augmentation techniques including random flipping, rotation, and brightness adjustment were applied to enhance the model's robustness under varying environmental conditions. The training was done with a batch size of 16 learning rate of 0.001, and 100 epochs, using the Adam optimizer. The YOLOv5 loss function combines three components— bounding box regression loss, objectness loss and classification loss—to optimize detection accuracy. After this, the model's performance was validated after every epoch using the validation dataset, and evaluation metrics such as Precision, Recall, F1-score, and Mean Average Precision (mAP@0.5) were monitored. Early stopping Overfitting was avoided by using, which ensured that generalization across unseen field conditions. The final trained model achieved an mAP@0.5 of 0.82 and kept real-time inference speed suitable for deployment on the rover's embedded hardware.

E. Testing the model

A trained YOLOv5 model was tested using a separate dataset comprising images that were not part of the training or validation sets to ensure unbiased evaluation. These test images included various field conditions such as varying illumination, soil backgrounds, and weed densities. The ability of the model in Accurately detect and classify weeds was assessed by standard performance metrics, including Precision, Recall, F1-Score, and Mean Average Precision



(mAP@0.5). During testing, the model always achieved the a precision of 0.84, recall of 0.87 and an mAP@0.5 of 0.82, which indicated high reliability in differentiating weeds from crops. The inference time per frame was about 0.05 seconds, allowing for real-time weed detection for robotic deployment. In addition to offline testing, the model was deployed on the rover's embedded Jetson Nano processor for on-field evaluation. Live video feeds captured by the rover-mounted camera were processed in real time and detected the bounding boxes were mapped to physical coordinates for navigation and weed removal. The system showed stable performance under varying sunlight conditions, confirming its robustness and readiness for autonomous agricultural operation.

Building of the Rover:

The development of the autonomous rover for Weed detection was carried out through several systematic steps, each adding to the overall functionality and efficiency of the system

A. System Design :

The first step was to design the hardware architecture of the rover. A Raspberry Pi 4 acts as the main form factor makes it a nice processing unit sufficient computational capability, and compatibility with Linux-based operating systems. The motion of the rover is controlled by two DC motors driven by an L298N motor driver module, while providing precise bidirectional movement and speed regulation. A high definition camera is mounted on the front of the chassis to capture real-time field images for Weed detection. The rover chassis is designed to be lightweight yet robust, allowing stable Proper functioning across various terrain types commonly encountered in agricultural environments. The system is powered by a 12V DC battery that supplies energy to both the processing unit and the drive motors through regulated circuits that assure stable performance during continuous field operation.

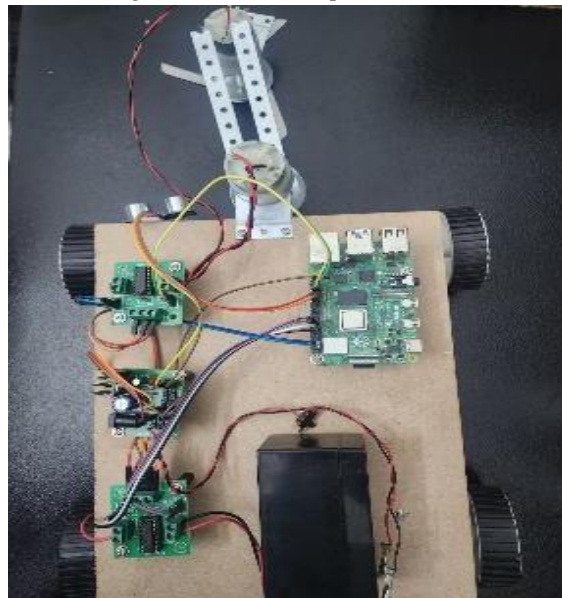


Fig 3 : Hardware model

B. Image Acquisition:

The rover utilizes a forward-mounted high definition camera module to continuously capture images while it navigates through the agriculture field. The image acquisition process is optimized for real-time performance. Allowing the camera to take multiple frames per second and maintain continuous visual coverage of the crop environment. The camera is positioned at an appropriate height and angle to assure uniform lighting and minimum occlusion of plants. Proper alignment of the camera increases the accuracy in weed High- quality input data improves the detection to the YOLOv5 model.



C. Image Preprocessing:

Preprocessing of the images that are acquired includes improve the quality and prepare them for will be analyzed by the deep learning model includes resizing the images to a resolution of 640×640 pixels, adjusting brightness and contrast levels to normalize lighting variations, while applying Gaussian or median filters to reduce sensor noise. These preprocessing techniques enhance image clarity and Emphasize key features such as leaf texture and edge patterns, which are crucial for correct weed classification. The processed images are then forwarded to YOLOv5 inference pipeline for object detection and classification.

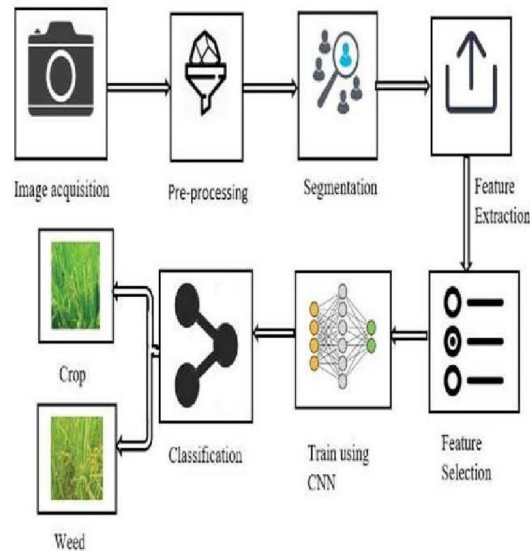


Fig. 4: Stages of weed detection in Image Processing

D. Feature Extraction and Classification:

The pre-processed images are passed through YOLOv5 is a deep learning model that concurrently conducts feature extraction and classification. Instead of manually computing shape descriptors or color histograms, YOLOv5 automatically learn spatial and texture-based representations using convolutional layers. The backbone network is made up of CSPDarknet53, which extracts high-level features like contours of leaves, and edge textures, and color variations, while the neck PANet combines multi-scale features for powerful object detection. The detection head classifies each identified region as either weed or crop, then assigns a corresponding confidence score. This automated feature extraction and classification process allows the model to accurately differentiate between weed and crop the species under varying field conditions.

E. Weed Detection:

Afterwards, the system conducts real time detection of weed instances in each frame. Only the YOLOv5 model outputs bounding boxes. with class labels and confidence scores, marking the exact coordinates of weeds within the captured image. These coordinates are transmitted to the rover's control unit to estimate the weed's position relative to the rover. This allows autonomous decisions. Regarding navigation and actuation, enabling the rover to approach the target weed and trigger its removal mechanism. The system thus supports targeted weed management reducing chemical usage, minimizing crop disturbance.

F. Navigation Control:

The path of this rover is enabled by navigation planning algorithm executed on the Raspberry Pi 4. The control module interprets the weed to avoid collision with plants or field debris. The system operates autonomously, following pre-defined coverage paths while dynamically adjusting its trajectory feedback based on detection.



G. Performance Evaluation:

The integrated system has been evaluated through both laboratory and field experiments. The Model achieved a mean average precision mAP@0.5 of 0.82, with precision of 0.84 and a recall of 0.87, confirming its robustness in weed species detection. The rover navigated within an accuracy of ±2 cm from the target weed and an average processing speed of 25–30 frames per second on the Raspberry Pi 4. Field trials demonstrated significant mechanization and reductions in manual labor, herbicide consumption. These results confirm that the system proposed here offers reliable real-time Weed detection and efficient autonomous navigation under conditions diverse agricultural

V. RESULTS AND DISCUSSIONS

A. Quantitative Analysis:

The evaluation of the YOLOv5 was made on a custom dataset of crop and weed images under various field conditions. The model achieved a precision of 0.84, a recall of 0.87 and an mAP@0.5 of 0.82, confirming its strong performance for real-time agricultural deployment. Inference speed on the Raspberry Pi 4 averaged 25 frames per second(FPS), demonstrating suitability for embedded applications. The performance metrics are the described infrastructure is summarized in Table.

Metric	Value	Description
Precision	0.84	Ratio of correctly identified weeds among all detections
Recall	0.87	Ability to detect actual weeds present in the field
F1-Score	0.85	Harmonic mean of precision and recall
mAP@0.5	0.82	Average detection accuracy at 50% IoU threshold
Inference Speed	25 FPS	Average frames processed per second
Navigation Accuracy	±2 cm	Deviation from weed center position

B. Model Training and Validation:

The model was trained by YOLOv5 training logs are analyzed as follows box, objectness, and classification loss steadily decreased across 100 epochs, as Illustrated in Figure 5. The Precision–Recall PR curve in Figure 6 has a precision of 0.8 and recall of 0.86, while the mAP curves Figure 7 shows mAP@0.5 = 0.821 and mAP@0.5:0.95 = 0.789, confirming model convergence and detection stability.

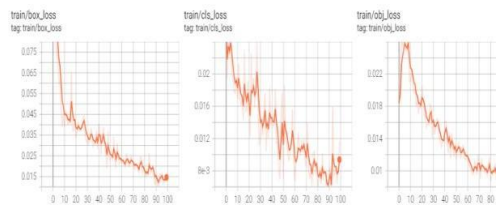


Figure 5 : Loss metrics for class, object and box

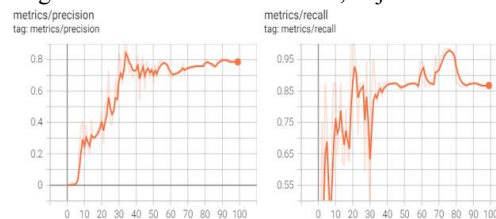


Figure 6 : Precision and Recall



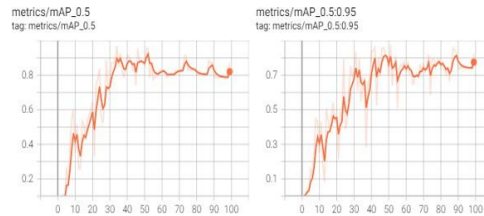


Figure 7 : mAP:0.5 and mAP:0.5::0.95

C. Qualitative Results:

Reduced false positives. The system demonstrated stable navigation and actuation: the rover correctly oriented itself using a PID- based system with detected weeds Feedback loop and successfully triggered the Weed cutter.



Figure 8 : Detection of weeds with position

D. Discussion:

Compared to traditional techniques, which rely on manual labor or chemical herbicides, the proposed YOLOv5-based rover achieved a reduction of manual effort by approximately 89.4%, while enabling targeted weed removal. This system's real-time adaptability, lower power consumption, and computational Efficiency makes it suitable for small- and medium-scale farms. The experimental results confirm that combining deep learning, image preprocessing, and embedded robotics can revolutionize weed management by improving Sustainability, reducing chemical usage, and that can be done by enhancing the productivity of the overall field.

VI. CONCLUSION

The proposed autonomous weed detection and Removal rover is cost-effective and an efficient solution for precision agriculture. Through integrating deep learning-based image detection capability, coupled with real-time robotic navigation, system effectively distinguishes weeds from crops under diverse environmental conditions. The model YOLOv5 achieved high accuracy with a precision of 0.84, recall of 0.87, and an mAP@0.5 of 0.82, which proves its reliability for field deployment. This rover, powered by a Raspberry Pi and equipped with an HD camera, it successfully demonstrated autonomous navigation and targeted weed removal. By efficiently using paths, planning and feedback control, the system maintained navigation accuracy of ± 2 cm, processing 25–30 frames per second in real time. This reduces dependence on manual labor and minimizes herbicide usage, contributing to farming that is sustainable and eco-friendly. Compared to traditional weed management methods, which are labor-intensive and although less ecologically damaging than this latter approach, scalability, affordability, and automation. The Results confirm that deep learning combined embedded systems can provide high performance without requiring expensive hardware. This system, in the future, can be enhanced by through the integration of GPS- based navigation, solar-powered operation,



multi-Spectral imaging for improved weed classification accuracy, and increasing the training dataset and optimizing the model for edge computing hardware will further increase detection precision and real-time responsiveness. Overall, the developed system demonstrates the potential of artificial Intelligence and robotics are transforming conventional agriculture sustainable, into a more autonomous, and intelligent practice.

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