Weed detection using YOLOv3 and elimination using organic weedicides with Live feed on Web App

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***Abstract*—The article discusses the pressing issues in agriculture, particularly highlighting the significance of detecting and categorizing weeds. Weeds pose a threat by competing with crops for vital nutrients, traditionally addressed through manual detection and herbicide application. However, recent technological progress has focused on automating weed detection using methods such as YOLOV3, a CNN-based object detection technique. In addition, the article introduces a fresh approach that utilizes linear actuators and organic weedicides for weed control. It evaluates this system's effectiveness in terms of preci- sion and dynamic intrarow weeding through various analyses and experimental trials, demonstrating high accuracy and efficiency in real field scenarios. The live video footage of weed detection and removal is also showcased on a web application, providing users with information on the number of weeds eliminated. This integration of technological and chemical solutions presents a promising strategy for managing weeds in agriculture.**

***Index Terms*—weed detection, crop, CNN, YOLO, dataset, digital farming, agriculture, deep learning, Dynamic intrarow weeding, linear actuators, parallel mechanism (PM) design, performance analysis, live feed, web app.**

I. Introduction

A. General Background

Agriculture has long served as the backbone of the global economy, feeding and sustaining the world's ever-growing population. Yet, the landscape of modern agriculture is continually evolving, posing a unique set of challenges. The demand for increased crop productivity coincides with the urgent need to minimize the environmental impact of farming practices. In response, precision agriculture has emerged as a transformative approach. This methodology involves the spatial scanning of key indicators of crop health, enabling the precise application of treatments such as herbicides, pesticides, and fertilizers. These treatments are administered only where they are required, conserving resources and reducing environmental harm.

Furthermore, the integration of robotics into agriculture is a pivotal development. Robotic systems are being increasingly recognized for their versatility and cost-effectiveness in automating labor-intensive tasks, a notable one being weed management. Weeds, despite the agricultural abundance, continue to undermine crop growth by siphoning away vital nutrients from cultivated plants. The relentless challenge of weed control has necessitated innovative farming practices, including advanced technologies and techniques.

B. Objectives

The central focus of this article revolves around the crit- ical issue of weed management. Firstly, it underscores the importance of precise weed detection. Identifying weeds accurately is crucial for targeted interventions while minimizing interference with desired crops, making weed detection the cornerstone of this endeavor.

Secondly, the article introduces an innovative approach using linear actuators and organic weedicides to tackle the ongoing challenge of weed management. This novel method replaces the conventional laser weeding system. It employs linear actuators for weed elimination operations, along with organic weedicides for effective control. The article provides detailed insights into this new approach, conducting thor- ough analyses covering various aspects such as kinematics, workspace, singularity, and dynamics. The ultimate goal is to evaluate the effectiveness and practicality of this system in real-world agricultural settings.

C. Scope

The scope of this article is both extensive and multifaceted, encompassing a range of critical components. At its core is the comprehensive evaluation of the introduced linear actuator system where we incorporate the use of linear actuators and eliminate weeds using the image obtained and organic weedicides by moving the linear actuators to a specific point.

The article has also checked onto the accuracy of weed and crop identification by using the datasets which consists of a total of 18,374 images of both cops and weeds and made the algorithm to learn and classify them perfectly. Since we're keeping the camera underneath the rover and the camera is too close to the target, the accuracy is always high with it being greater than 89%.

These statistics underscore the system's remarkable potential in real-world field scenarios, where the complex interplay of variables can often challenge even the most advanced technologies. The proposed organic weeding system using rover not only fulfills its intended purpose but also holds significant promise for contributing to the broader advancement of modern healthy and safe agricultural practices, further supporting the essential role of agriculture in the global economy.

II. Literature Survey

Several papers with similar goals aligned to the paper were selected and were found to be useful for the project. The project needed a definitive solution regarding what paper uses both AI, machine learning, IOT and networking and the paper titled "Design, Development and Evaluation of an Intelligent Animal Repelling System for Crop Protection Based on Embedded Edge-AI" [1] was referred. This paper talks about animal repelling using image processing methods, AI and cloud networking to repel animals using Ultrasonic sound waves. We also needed a paper later on to study the algorithms perfect for our project, for that the paper titles, "Few-Shot Learning for Small Impurities in Tobacco Stems With Improved YOLOv7" [2], "Weed Plant Detection from Agricultural Field Images using YOLOv3 Algorithm" [3] were compared and analysed further using the paper, "YOLO-Based Deep Learning Framework for Olive Fruit Fly Detection and Counting" [4]. The above paper talks about which YOLO algorithm needs to be used to detect the fruit fly and also compares the standard deviation of the RGB used in the camera image to detect and classify the flies.

Other than the above papers, the paper titled "Technological revolutions in smart farming: Current trends, challenges & future directions" [5] was also studied in detail to learn about the current farming trends and the usage of Embedded AI technology and cloud to manage the data efficiently. This paper also talks about all of the deep learning techniques, it's impact in smart farming, IOT and it's impacts in smart farming, Robotics and autonomous systems and it's impacts in smart farming and also about Cloud-fog-edge computing and it's impacts in smart farming. These papers collectively helped in both detection and message transmission to the web page.

We also needed a paper exclusive for the elimination of weeds, for that we referred to, "A Novel Two-Degree-of-Freedom Gimbal for Dynamic Laser Weeding: Design, Analysis, and Experimentation" [6] which focuses on the weed detection, classification and elimination using laser. The paper uses a gimbal to rotate the laser around 270 degrees using the formulas using the formulas they've crested and the models are experimented, studied and analysed repeatedly to attain perfection. Although our paper uses Linear actuators rather than gimbal, the formulas used to evaluate the weeds' location is valid for our project and can be used.

III. Methodology

Weed manipulation is essential in agriculture; those are unwelcomed by farmers due to the fact they motive a number of troubles inside the crop. Among its poor outcomes is the infection of production, breeding floor for bugs and sicknesses will increase irrigation and promotes the boom of different pests' costs. We can come across the presence of those weeds through tracking them.

Figure 1 depicts the weed detection part of the proposed system. First, we extract and label the images in the dataset to generate an annotation file to convert the CSV files into .txt files. Further, we train the images in our dataset using the proposed training model to classify the image files. Once the features are extracted the YOLO model creates a scan window or box around the detected object and it recognizes and provides the accurate result.

Then after that we use a linear actuators coupled with weedicides to one end of the linear actuator to eliminate the detected weeds using YOLOv3 algorithm. This method eliminates weeds one row at a time. This information on number weeds detected and eliminated are sent to the user via web app along with live footage.

A. CNN Architecture

The CNN has been an increasing number of utilized in agriculture because of its sturdy illustration cap potential of photo features. A Convolutional Neural Network (CNN) is a set of Deep Learning rules that can accumulate a photo, dele- gate significance (teachable weights and biases) to numerous aspects inside the photo, and distinguish from one another. While filters in primitive strategies are hand-engineered, CNN can research those filters/traits with sufficient training.

The fundamental building blocks of CNNs include various layers that perform specific operations:

1) Convolutional Layer: This layer performs the main operation in a CNN by applying a set of learnable filters or kernels to the input data, performing convolution operations. Each filter detects different features within the input image by sliding over the entire image and producing feature maps.

2) Activation Function: Typically, a non-linear activation function like ReLU (Rectified Linear Activation) is applied element-wise to the output of the convolutional layer. It introduces non-linearity to the network and helps in learning complex patterns.

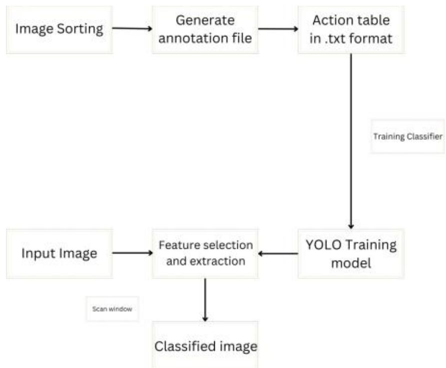
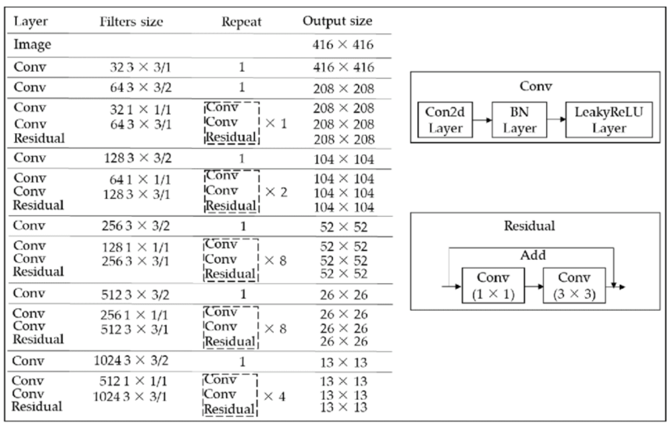


Fig. 1. CNN Architecture



Layer	Filters size	Repeat	Output size
Image			416 × 416
Conv	32 3 × 3/1	1	416 × 416
Conv	64 3 × 3/2	1	208 × 208
Conv Conv Residual	32 1 × 1/1 64 3 × 3/1	Conv Conv × 1 Residual	208 × 208 208 × 208 208 × 208
Conv	128 3 × 3/2	1	104 × 104
Conv Conv Residual	64 1 × 1/1 128 3 × 3/1	Conv Conv × 2 Residual	104 × 104 104 × 104 104 × 104
Conv	256 3 × 3/2	1	52 × 52
Conv Conv Residual	128 1 × 1/1 256 3 × 3/1	Conv Conv × 8 Residual	52 × 52 52 × 52 52 × 52
Conv	512 3 × 3/2	1	26 × 26
Conv Conv Residual	256 1 × 1/1 512 3 × 3/1	Conv Conv × 8 Residual	26 × 26 26 × 26 26 × 26
Conv	1024 3 × 3/2	1	13 × 13
Conv Conv Residual	512 1 × 1/1 1024 3 × 3/1	Conv Conv × 4 Residual	13 × 13 13 × 13 13 × 13

Fig. 2. CNN convolutional layers

3) Pooling (Subsampling) Layer: This layer reduces the spatial dimensions of the convolved feature maps while retaining important information. Max pooling and average pooling are common pooling techniques used to downsample feature maps by taking the maximum or average value within a defined window.

4) Fully Connected (Dense) Layer: These layers are typically present at the end of the CNN architecture and perform classification or regression tasks. Neurons in a fully connected layer have connections to all activations in the previous layer, and they help in learning the relationships between high-level features and the output labels.

5) Dropout Layer: Dropout is a regularization technique used to prevent overfitting. It randomly drops (sets to zero) a fraction of neurons during training, which forces the network to learn more robust features and prevents it from relying too much on specific neurons.

6) Flattening Layer: This layer is used to convert the multi-dimensional feature maps into a one-dimensional vector, which can be fed into a fully connected layer for classification or regression.

7) Batch Normalization Layer: It normalizes the activations of each layer to improve the training speed and stability. It reduces the internal covariate shift by normalizing the output of the activation functions.

These layers are typically arranged in a sequential manner to form the CNN architecture. Multiple convolutional layers followed by pooling layers are stacked to create a deeper network capable of learning intricate features at various levels of abstraction. This hierarchical learning allows CNNs to achieve state-of-the-art performance in tasks like image recognition, object detection, and image segmentation.

B. YOLOv3

YOLO (You Only Look Once) is a popular object detec- tion algorithm known for its speed and accuracy. YOLOv3 is the third iteration of the YOLO series, an advancement over its predecessors, YOLO and YOLOv2. This architecture, designed by Joseph Redmon and Ali Farhadi, introduces improvements in accuracy and speed for real-time object detection tasks.

These are some features of YOLOv3:

1) Single-stage Detection: YOLOv3 follows a single-stage detection approach, meaning it directly predicts bounding boxes and class probabilities from a single pass through the neural network, unlike two-stage detectors (e.g., Faster R-CNN) that first propose regions of interest and then refine detections.

2) Backbone Network: YOLOv3 employs a Darknet-53 architecture as its backbone. Darknet-53 is a deep neural network consisting of 53 convolutional layers that serve as the feature extractor. It extracts features from the input image, which are then used for detection.

3) Feature Pyramid: YOLOv3 utilizes a feature pyramid network (FPN) to extract features at different scales. This helps in detecting objects of varying sizes by utilizing features from multiple layers with different resolutions.

4) Detection at Multiple Scales: YOLOv3 predicts detections at three different scales, allowing the network to detect objects of different sizes. The predictions are made at three different output layers in the network.

5) Bounding Box Prediction: YOLOv3 predicts bounding boxes using a grid cell approach. The input image is divided into a grid, and each grid cell predicts bounding boxes based on predefined anchor boxes. This method allows YOLOv3 to efficiently handle object detection across the entire image.

6) Class Prediction: Alongside bounding box predictions, YOLOv3 also predicts class probabilities for each bounding box. This enables the network to recognize and classify multiple objects present in the image.

7) Non-Maximum Suppression (NMS): After the initial predictions, YOLOv3 employs NMS to refine the bounding box detections by suppressing multiple overlapping boxes and keeping only the most confident ones.

YOLOv3 strikes a balance between accuracy and real-time performance, making it suitable for various applications like object detection in videos, surveillance, autonomous vehicles, and more. Its ability to detect objects across different scales and its single-pass processing speed have contributed to its popularity in the field of computer vision.

C. YOLOv3 vs other YOLO models

Aside from the fact that YOLOv3 uses darknet framework and the others use PyTorch, Tensorflow, etc, YOLOv3 is proven to be much faster than YOLOv5 and YOLOv4 which are it's successors. YOLOv3 is a model much better than the other previous YOLO models which use a different framework. The accuracy and the time taken were improved by a lot in YOLOv3.

D. Modules used(Raspberry Pi 4 B)

Fig. 3. Raspberry Pi mopdule

Raspberry Pi 4 B is a powerful single-board computer (SBC) that can be effectively utilized for object detection tasks. Its enhanced processing power and memory capacity make it suitable for running object detection algorithms, enabling real-time performance and accurate results. This a much better version of Raspberry Pi than the most recent version, Raspberry Pi 5. The difference from using Raspberry Pi 4 B from Raspberry Pi 5 is that the object detection is much faster and can take loads of memory in Raspberry Pi 4 B. This version is highly compatible with object detection, especially real-time object detection. These are the key features of Raspberry Pi 4 B,

1) Powerful Quad-Core Processor: Raspberry Pi 4 B boasts a quad-core Broadcom BCM2837 Cortex-A72 processor, operating at 1.5GHz. This powerful processor can efficiently handle the computational demands of object detection algorithms, ensuring smooth performance.

2) Ample Memory: Raspberry Pi 4 B comes with 2GB, 4GB, or 8GB of LPDDR4 memory, providing sufficient re- sources for loading and running object detection models. The higher memory configurations allow for processing larger models and handling more complex object detection tasks.

3) Versatile Connectivity Options: Raspberry Pi 4 B offers a variety of connectivity options, including Gigabit Ethernet, dual-band Wi-Fi, and Bluetooth 5.0. These connections enable the Raspberry Pi to communicate with other devices, such as sensors and cameras, facilitating data acquisition for object detection tasks.

4) Multiple Camera Support: Raspberry Pi 4 B supports multiple camera interfaces, including the dedicated MIPI CSI-2 connector for the Raspberry Pi Camera Module. This allows for the integration of multiple cameras, enabling more comprehensive object detection coverage.

5) Hardware Acceleration: Raspberry Pi 4 B features hardware acceleration for various multimedia tasks, including video encoding and decoding. This hardware acceleration can improve the efficiency of object detection algorithms that involve video processing.

6) Open-Source Software Support: Raspberry Pi 4 B benefits from a vast ecosystem of open-source software libraries and frameworks, including TensorFlow Lite, OpenCV, and PyTorch. These libraries provide the necessary tools for developing and deploying object detection applications on the Raspberry Pi platform.

E. Arduino UNO

Fig. 4. Arduino UNO

Arduino UNO is a widely used microcontroller board based on the ATmega328P chip, offering simplicity and versatility for electronic projects. With 14 digital input/output pins, 6 PWM outputs, and 6 analog inputs, it provides ample connectivity options for interfacing with sensors, displays, and actuators. Arduino UNO supports various communication interfaces such as UART, SPI, and I2C, facilitating seamless communication with other devices. Its USB interface allows for easy programming and power supply, while the Arduino IDE offers a user-friendly environment for writing, compiling, and uploading code. Being open-source hardware and soft- ware, Arduino UNO encourages community collaboration and innovation, making it suitable for robotics, home automation, IoT applications, education, and prototyping.

When Arduino UNO is coupled with Raspberry Pi 4B in a rover, their combined capabilities enable a wide range of functionalities, enhancing the rover's overall performance and versatility. Here's what Arduino UNO and Raspberry Pi 4B can accomplish together in a rover:

1) Sensor Fusion: Arduino UNO can handle real-time sensor data acquisition and low-level control tasks, while Raspberry Pi 4B processes and analyzes sensor data with more computational power. By combining their capabilities, the rover can achieve sensor fusion, integrating data from multiple sensors such as cameras, lidars, and IMUs to create a more comprehensive understanding of its surroundings.

2) Navigation and Path Planning: Arduino UNO can manage basic navigation tasks such as motor control and obstacle detection, while Raspberry Pi 4B handles higher-level navigation algorithms and path planning. Together, they enable the rover to navigate autonomously, avoiding obstacles and following predefined routes or mission objectives.

3) Communication Interface: Raspberry Pi 4B can serve as the communication hub, handling wireless communication with ground stations, remote control consoles, or other rovers, while Arduino UNO manages local communication protocols and interfaces with onboard sensors and actuators. This setup facilitates seamless data exchange and coordination between the rover and external systems.

4) Task Execution and Payload Control: Raspberry Pi 4B can execute complex task algorithms, process image data, and control payload systems such as cameras, sensors, and robotic arms. Arduino UNO assists by coordinating low- level control tasks and interfacing with hardware peripherals, ensuring precise and responsive control of payload operations.

5) Fault Tolerance and Redundancy: By distributing control tasks between Arduino UNO and Raspberry Pi 4B, the rover gains redundancy and fault tolerance. If one system fails or encounters an error, the other can continue to operate, preventing mission failure and ensuring the rover's reliability in challenging environments.

6) Power Management and Efficiency: Arduino UNO can manage power distribution and monitor battery levels, while Raspberry Pi 4B optimizes power consumption and efficiency by regulating processor performance and peripheral usage. This collaboration helps maximize battery life and extend the rover's operational endurance during missions.

7) Data Logging and Analysis: Raspberry Pi 4B can store and process large volumes of sensor data, while Arduino UNO handles real-time data logging and basic data preprocessing tasks. Together, they enable the rover to collect, analyze, and transmit valuable telemetry data for post-mission analysis and decision-making.

Overall, coupling Arduino UNO with Raspberry Pi 4B in a rover harnesses the strengths of each platform, enabling the rover to perform complex tasks autonomously, communicate effectively with external systems, and adapt to dynamic environments with agility and reliability. This integration enhances the rover's capabilities and expands its potential applications in exploration, research, surveillance, and other fields.

IV. Proposed System

For the weed detection and elimination project using a rover equipped with 2 linear actuators

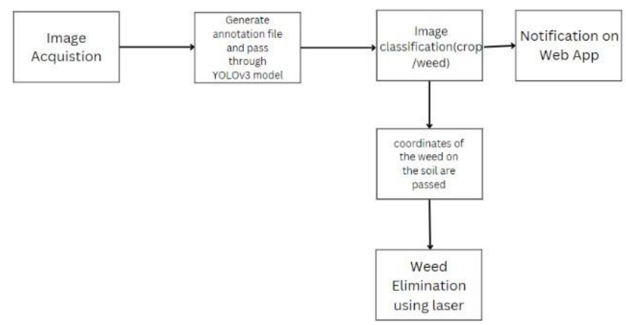


Fig. 5. Architecture

On the software side, several algorithms need develop- ment. This includes creating a weed detection algorithm using computer vision or deep learning models to process images from the rover's cameras. The algorithm should identify and differentiate weeds from the background by leveraging distinct features or patterns. Mapping and localization algorithms are necessary for mapping the rover's environment, localizing weed positions, and creating a virtual map to keep track of detected weed locations. The images in total used to make the YOLOv3 algorithm to learn to differentiate consists of a total of 18,374 images. Control algorithms are essential for managing rover movements, Linear actuator orientation, and nozzle activation based on weed detection. The rover's movement speed is calculated by testing it repeatedly and an average is found. This speed is noted for positioning of the nozzle on the top of the weed. Furthermore, the parts are checked regularly for any threat of danger involving repair or fix.

The workflow of the project involves the rover autonomously or semi-autonomously navigating the environment, scanning it using onboard sensors and cameras. Upon detecting potential weed patches, the rover marks their locations on its map. To eliminate weeds, the rover navigates to the detected patches, aligns the linear actuator mounted nozzle containing organic weedicides for precise targeting, and activates the nozzle to eliminate weeds. Furthermore, a web-based interface needs development to monitor rover operations remotely, display detected weeds on the user profile and warns the user of any potential threats, and update the status of eliminated weeds in real-time.

The project also makes use of one more module, Arduino UNO to further divide and simplify the processing done in the rover. This resolves the overheating issue within the Raspberry Pi unit. This also makes sure that weeds are eliminated as fast possible. The only down-side of implementing this is the fact that it needs more power to work but considering the safety of the components, this idea is infact more reliable for the project.

The rover is also subjected to several environmental conditions such as humid, cold, hot and damp weather conditions and are checked thoroughly under artificial environmental conditions to further increase the success rate of the project. The project is checked thoroughly for any inconsistencies so that it can be used in real life more efficiently and easily for farmers.

Throughout the project, various challenges need consideration. Ensuring safety protocols for laser usage to prevent harm to humans or unintended targets is crucial. Achieving precision in weed detection and elimination under varying environmental conditions poses a challenge. Additionally, de- veloping robust navigation and obstacle avoidance algorithms for the rover and managing power consumption for prolonged operation are critical factors that need attention. Collaboration between hardware engineers, software developers, and robotics experts will be fundamental for successful implementation, requiring testing and iterative refinement to enhance efficiency and accuracy.

A. Figures and Tables

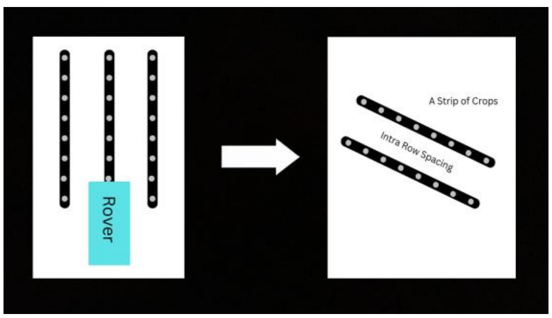


Fig. 6.

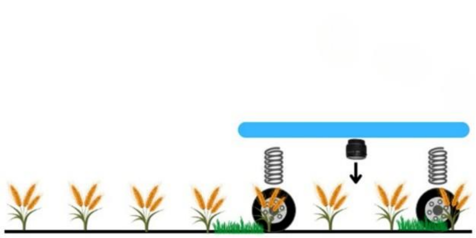


Fig. 7. Working of rover

Fig. 8. Nema 17 stepper motor

Fig. 9. Linear actuator

Fig. 10. Chassis

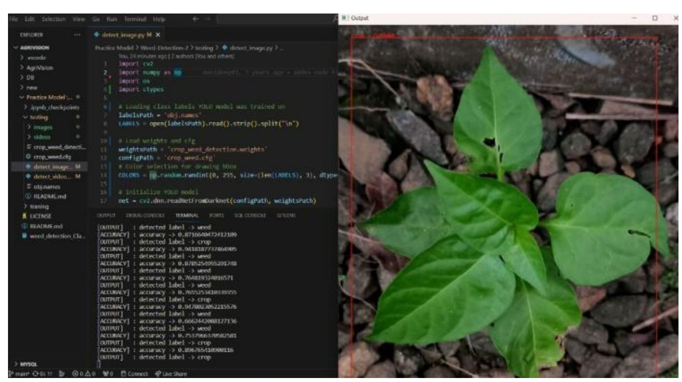


Fig. 11. Crop detection

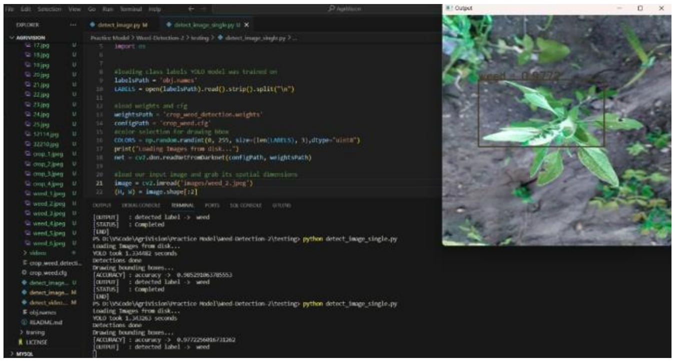


Fig. 12. Weed detection

V. Conclusion

The fusion of linear actuators, organic weedicides, the Raspberry Pi 4B, live web feed, and extensive datasets represents a significant advancement in weed management for agriculture. Each component plays a crucial role in enhancing efficiency, sustainability, and effectiveness in weed control practices.

The integration of linear actuators allows for precise and automated weed elimination, reducing the need for manual labor and increasing operational efficiency. This automation streamlines weed management processes and enables farmers to achieve targeted weed control while minimizing disruption to desirable crops.

Organic weedicides, incorporated into the system, offer an environmentally friendly alternative to conventional herbicides. By utilizing natural ingredients derived from plant extracts, these weedicides pose minimal risk to soil health, biodiversity, and human health. This sustainable approach to weed control aligns with consumer preferences for eco-friendly farming practices and contributes to the overall resilience of agricultural systems.

The Raspberry Pi 4B serves as the central control unit, facilitating real-time decision-making and coordination among various components. Through sensors and image processing algorithms, it enables accurate weed detection and classification, optimizing the deployment of linear actuators for targeted weed elimination.

The live web feed functionality provides farmers with real-time monitoring and control over weed management activities. This feature allows for immediate adjustments based on feedback and ensures optimal outcomes, enhancing operational transparency and adaptability.

Lastly, the extensive datasets comprising 18,374 images serve as a valuable resource for training and refining the system's algorithms. By exposing the system to a diverse range of real-world scenarios and weed species, the dataset ensures robust performance across various agricultural environments and conditions, ultimately improving the system's accuracy and reliability.

In summary, the integration of these components represents a holistic and data-driven approach to weed management in agriculture. By leveraging technology, sustainable practices, and real-time monitoring, farmers can achieve greater efficiency, productivity, and environmental sustainability in their weed control efforts, ultimately contributing to the long-term viability and resilience of agricultural systems.

References

[1] Adami, Davide & Ojo, Mike & Giordano, Stefano. (2021). Design, Development and Evaluation of an Intelligent Animal Repelling System for Crop Protection Based on Embedded Edge-AI. IEEE Access. PP. 1-1. 10.1109/ACCESS.2021.3114503.

[2] Xue, Sheng & Zhenye, Li & Wu, Rui & Zhu, Tingting & Yuan, Yangchun & Ni, Chao. (2023). Few-Shot Learning for Small Impurities in Tobacco Stems With Improved YOLOv7. IEEE Access. PP. 1-1. 10.1109/ACCESS.2023.3275023.

[3] Dandekar, Yukta & Shinde, Kshitija & Gangan, Jai & Firdausi, Sabil & Bharne,. (2022). Weed Plant Detection from Agricultural Field Images using YOLOv3 Algorithm. 1-4. 10.1109/ICCUBEA54992.2022.10011010.

[4] Mamdouh, Nariman& Khattab, Ahmed. (2021). YOLO-Based Deep Learning Framework for Olive Fruit Fly Detection and Counting. IEEE Access. PP. 1-1. 10.1109/ACCESS.2021.3088075.

[5] Sharma, Vivek & Tripathi, Ashish & Mittal, Himanshu. (2022). Technological revolutions in smart farming: Current trends, challenges & future directions. Computers and Electronics in Agriculture. 201. 107217. 10.1016/j.compag.2022.107217.

[6] Wang, Mingfeng & Leal-Naranjo, Jose´ & Ceccarelli, Marco & Blackmore, Simon. (2022). A Novel Two-Degree-of-Freedom Gimbal for Dynamic Laser Weeding: Design, Analysis, and Experimentation. IEEE/ASME Transactions on Mechatronics. PP. 1-11. 10.1109/TMECH.2022.3169593.