

WEED DETECTION AND REMOVAL USING LASER BEAMS

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ABSTRACT

It encompasses the release of a revolutionary laser-pumping weed detection and killing system. The system will change the green world of agriculture. The system detects the weeds that are eating the crops in real-time with absolute precision and kills weeds separately. Close-up live field images are captured through high-definition cameras and sensors and inputted through high-order machine learning algorithms to detect weeds accurately. This results in weed and crop recognition by the system, whereby weeds are removed automatically.

Laser beams sensed and calibrated are also utilized in weed cell structures killing to successfully kill them without damaging surrounding crops planted around them. Laser technology is a replacement for traditional weed control methods with their degradative effect on soil structure, e.g., excessive use of herbicides or degradative mechanical weeding. In its assault on the destruction of weeds at the cell level, the system is not degradable to soil composition overall and soil integrity is preserved while long-term sustainability in agriculture is also guaranteed.

In addition to providing environmental advantage, the system also cuts the cost of weeding significantly using less labor and herbicide reliance. The farmers are therefore better positioned to manage the propagation of weeds, lower the cost of the operations, and maximize the output of the crops. Generally, the new weed detection and weeding system is a cost-effective, eco-friendly, sustainable system that enhances sustainable agriculture, conserves the soil, and offers a low-cost, scalable solution for weeding in vast farms.

Keywords: Laser Weeding, Weed Detection, Precision Farming, High-Resolution Imagery, Sustainable Farming.

I. INTRODUCTION

Unwanted vegetation growing above the farm land competing with crops for sunlight, water, and nutrients are referred to as weeds. Weeds can prevent crop growth from happening, thus leading to lower yields and increased cost of production. Mechanical tillage, hand weeding, and herbicides — chemical, bio, and synthetic — were earlier methods practiced by individuals as cultivators to control weeds from their lands. Even though these measures might be effective, they have negative effects such as environmental contamination, the emergence of weed plants resistant to herbicides, and even killing beneficial insects and the soil.

As agriculture across the globe continues to evolve, the farming and cultivation become more sustainable and environmentally friendly. It is thus essential to discover new technologies such as alternative technologies, among which laser based technologies for weed detection and removal are also included. Advanced detection and imaging technologies are used to differentiate between crops and weeds, as per this process, which allows for targeting precisely at the target area. Farmers can use lasers to eliminate weeds from the crops, without destroying the neighboring crops without changing the balance of the environment and without providing healthier farm environments.

Besides this, it is also part of the overall trend of precision agriculture, which is driven by the development of laser technology in agriculture. The application of these data-driven observations and automatic system to maximize the farming efficiency and productivity is this method. Laser weed control is applied in the agricultural operation to prevent wasteful use of chemical substances, enhance the optimization of resources, and generally enhance the plant health. The objective of this project—following the application of laser beams in the identification and elimination of weeds—will be to realize how efficient and feasible laser beams are in the process, and assist in the development of more eco-friendly and effective agricultural technologies in accordance with the current agricultural challenges.

II. REVIEW OF LITERATURE SURVEY

The field of automated weed recognition has also made tremendous progress through the application of machine learning and deep learning principles. Certain studies are being pursued on AI-platforms for enhanced accuracy and performance of weed detection and elimination from crop fields.

[1] Deep learning was utilized for building a CNN model for weed classification with effective discrimination between crops and weeds. Experimental application in agriculture was demonstrated in the research using the potential of CNNs.

[2] YOLOv8 was utilized for real-time weed detection from annotated bounding box datasets with high-precision localization. Effective performance under varied environmental conditions was shown through the outcome of the experiment.

[3] Following attempts to enhance feature definition towards background removal issues, U2-Net was applied to weed classification issues. Background subtraction was set as a prerequisite for enhanced classification accuracy.

[4] Hybrid texture classification based on Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) was proposed. Statistically computed features had the potential to enhance classification performance using retained spatial and local texture information.

[5] Transfer learning-based methods employing pre-trained VGG16 and DenseNet models were also explored for weed species classification. The research proved that utilization of pre-trained CNN models led to high classification accuracy, particularly for sparse training sets.

[6] Edge detection techniques, including the Prewitt filter, were utilized to improve shape-based weed classification using structural feature extraction. The process allowed for effective discrimination between weed types using contour and gradient analysis.

[7] In the management of the class imbalance problem, Synthetic Minority Over-sampling Technique (SMOTE) was used in the creation of artificial weed samples. Data augmentation by using SMOTE has been shown to improve the generalization and the classification rate of the model to a large extent, based on the study.

[8] Real-time crop weed identification was done through a mobile app utilizing a deep learning model. The research proved that implementing AI-powered weed detection technology on edge devices was feasible to be used in actual crops.

In general, these papers describe how deep learning has been utilized to develop standalone weed recognition models and how the roles of CNN models, feature extraction techniques, and data augmentation strategies towards the achievement of model robustness and classification accuracy have been dealt with.

III. EXISTING SYSTEM

Various contemporary enclosures of weed discovery and evacuation have developed sowing capacities to rethink the agricultural landscape. The time to need is to invest and develop agricultural technologies in the shortest time span, effectiveness and sustainability. Conventional methods mainly cover from cultural practices such as mechanical weeding to chemical herbicides. One of the mechanical processes of weeding is the destruction of weeds through ploughing, hoeing, etc, but chemical processes depend on herbicides for killing unwanted plants. But they - though useful - can be this so very labor-intensive, environment-destroying process that is prone to problems such as resistance to herbicides. To overcome such limitations of the traditional methods, computer vision + machine learning based automated systems based on novel imaging technologies have been developed. Such systems have been utilizing across years computer vision + machine learning based algorithms to identify and discriminate between crops and weeds. Multispectral/hyperspectral imaging, for instance, is employed by some systems to image their unique spectral signatures of plant species that allow discrimination at the species level. Robots to be used on autonomous field trips, employing such imaging devices integrated into devices that utilize apply herbicides where its required OR utilizing mechanical energy to uproot weeds. But such approaches are also centered on chemical applications which are harmful to the environment. The laser technology is relatively new as an alternative approach to managing weed. Laser technology-based systems Advanced sensors and algorithms detect and decide rapidly with sensing and deciding at high speed. These examine and assess the data gathered in real time so that they can, in turn, detect and differentiate between what is a weed and what is a wanted plant (or foliage, or leaves.). Identify unwanted plants based on visual characteristics. Now controlled by scientists, lasers can find and incinerate weeds without any damage to the surrounding crops. Some test systems, prototypes, and a few commercial systems have been tested to deliver high accuracy and low chemical usage. Commercial manufacturing of laser-based systems is still in the offing. Although recently discovered in California and

brought into readiness for environmentally friendly early use, they are a step ahead in renewable methods of weed control conforming to precision farming dictates.

IV. PROPOSED SYSTEM

The approach is laser technology hybridization with deep-learning based weed detection to enable accurate autonomous weeding. The approach tackles real-time gray-level and resampled preprocessed images, applies YOLOv8 to enable accurate recognition of weeds with accuracy, enhances classification with GLCM, LBP, CNN structures, and feature extraction based on image moments, and class imbalance handling using SMOTE. The approach employs Prewitt edge detection to enable better shape-based feature extraction. These weeds are removed by utilizing the help of a laser beam to facilitate sustainable non-chemical weed removal. The system also has Streamlit-based user input and monitoring in real-time for a low-cost, scalable, and sustainable approach to farming in modern times.

Algorithms used:

1. YOLO for Weed Detection:

YOLO algorithm is employed for real-time weed detection by scanning the entire image in a single pass. YOLO identifies weeds and computes the coordinates of the bounding box to be used.

2. Grid-Based Image Segmentation:

Detected frame is separated into a grid to improve the detection accuracy and the smallest weeds are identified with the highest priority and detected flawlessly.

3. Midpoint Calculation Algorithm:

Once the weeds are detected, its center point is computed from the bounding box coordinates to place the laser at the center point of the weed.

4. Coordinate Mapping and Transformation:

Coordinates in the physical world are mapped from image coordinates by camera calibration and perspective correction to allow for accurate targeting of the laser.

5. NodeMCU Communication Protocol:

Weed coordinates are graphed using NodeMCU microcontroller and converted into servo motor movement instructions to hit exactly.

6. Servo Motor Control Algorithm:

The X and Y axis servo motors are controlled based on where the weed is located. The Pulse Width Modulation (PWM) is employed in a manner that it manages the motion of the motor so that the motors are coordinated.

7. Laser Activation and Targeting Algorithm:

Laser is fired for a specified duration after it had been directed to destroy the weed and agitate the rest of the environment as minimally as possible.

8. Verification and Retargeting Algorithm:

The frame is continuously supervised by the system once the lasers are used to determine whether the weed is eliminated. Yes, in case it is, then the laser is re-charged with minimal calibration until the weed is completely eliminated.

Such algorithms support one another in the detection and destruction of weeds independently with precision as well as minimal human intervention.

V. METHODOLOGY

It starts with the integration of basic hardware elements like the camera module used in live frame capture, the YOLO model used in detection of weeds from frames, the NodeMCU microcontroller, where computations and deployment happen, and the servo motors, which are used for the positioning of the laser into a position in which it can easily mark out weeds. The laser system is integrated here to be used.

It will just keep reading frames from the camera and processing them by decomposing all the frames into a grid structure during active operation. Segmenting allows it to decompose the frame into parts easily, thus providing more precision in weed detection. YOLO model is searching for any weed in the frame. And if it's not, then the system is simply waiting for the next frame to be read. But if a weed is in the way, then the system

computes its midpoint coordinates, and those are what are sent off to the NodeMCU so that it can make the laser turn on through this point. The calculated coordinates of the weeds are sent to the NodeMCU, to the control circuit.

It provides movement coordinates and commands the servo motors to drive the position on the X and Y axes such that the laser beam is placed on the target weed. It has the benefit of placing the laser on the weed with stunning precision without damaging surrounding plants or soil. Once it has homed into its rightful location, it is powered to release light energy onto the weed with the intention of destroying or killing the weed. Once it has fired a laser, the system checks whether the weed has been destroyed. The system rezeros the target of the laser, if need be, in an attempt to offer maximum precision in case the model still senses the weed.

The operation is done in such a manner that the operation totally erases the weed. When the weed is eliminated, the system is in check destruction state and does nothing unless a new frame is asked and the whole operation is performed on new weeds.

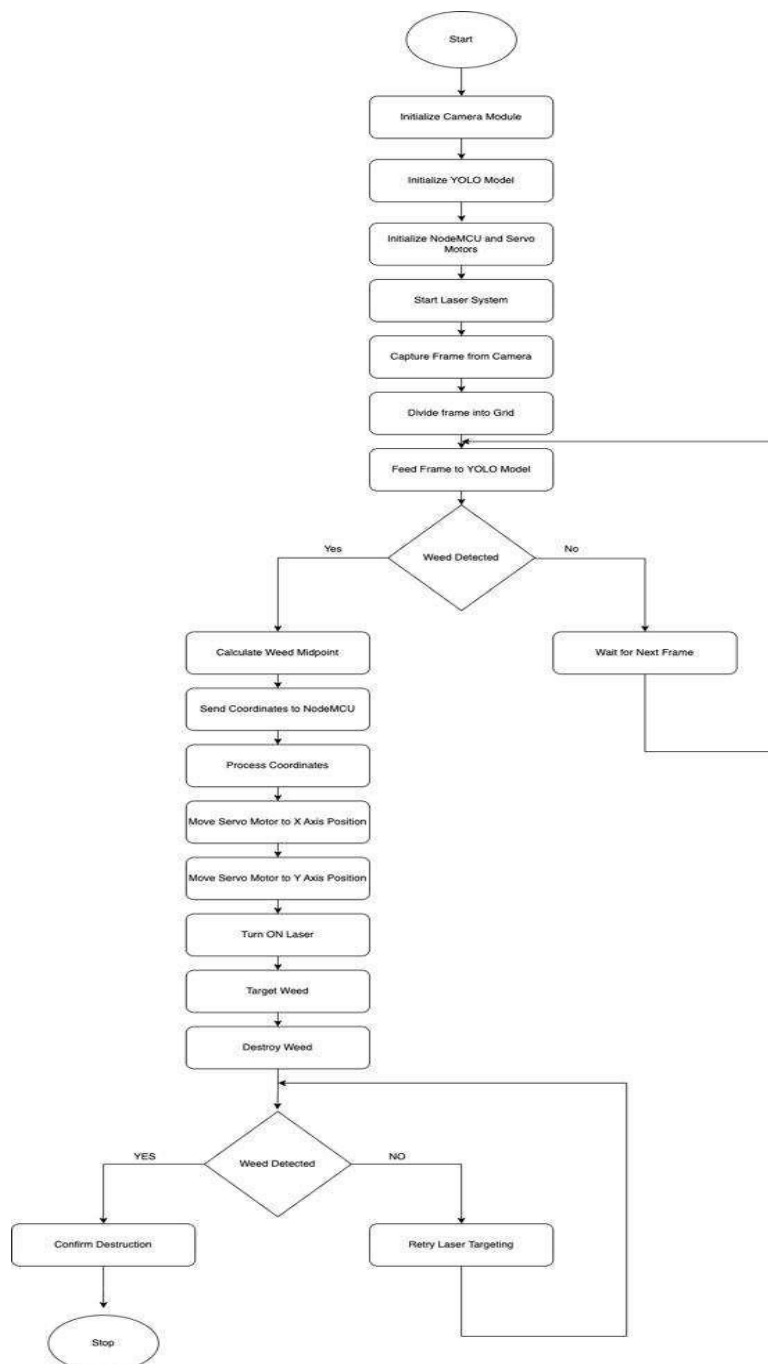


Figure 1: Flowchart of model

The flowchart describes the entire process of the weed detection and removal system step by step. It starts with the system initialization phase, where the hardware modules and the laser system are initialized. That is followed by the capture of the frame by a camera and the processing of the image by YOLO model in order to detect the weeds. The decision step has been depicted very well in the flowchart also.

Without the weed, the system will simply wait for the next frame to avoid wastage.

The flowchart guides the computation of the middle points of the weeds' coordinates and coordinate sending to the NodeMCU.

The flowchart guides the servo motor movement, where the system moves the X-axis and Y-axis motors to reflect the laser beam. Following the laser installation, activation of the laser and the setting of the direction of the laser beam to the weed and destruction of the weed is the second step. Each check step of the flowchart makes the system check and check infinitely if the weed is dead or not. Where the weed is un-cut, the flowchart causes the system to continue to try the laser targeting again and again until the weed is dead. Where the weed is cut, the system cuts it and it halts.

Together as a group, the flowchart details only the process and logical process sequence of weed identification and weed elimination, the way in which every module and decision node directs the system-building process to be its optimal best. It highlights the computer vision, microcontroller programming, servo motor control, and laser technology interplay dynamics towards synergy in unveiling an automated and optimized system of weed elimination.

Model building:

Weed detection and removal system utilizes systematic approach comprising deep learning-object detection, image processing, and laser targeting to obtain effective weed management. It begins with data acquisition and preprocessing wherein a USB camera images the field in real-time mode for image acquisition. Images undergo various processes of enhancement such as gray scale transformation, contrast enhancement, noise filtering, and elimination of background for the purpose of improved detection. Feature extraction techniques such as gray-level co-occurrence matrix (GLCM) and local binary pattern (LBP) enable discrimination between weeds and crops. The images are resized to 256×256 pixels prior to input to the detection model.

For weed detection purposes, the model is constructed with YOLOv8 as an object detection model based on CNN. The model is trained on a well-annotated dataset for bounding box value estimation and classification. Pre-trained weights assist in the biased toward feature extraction aspect using techniques such as synthetic minority over-sampling (SMOTE) for balancing of class distribution to assist in the detection based on the types of weeds equally.

The model is trained and evaluated on metrics such as mean intersection over union (mIoU), mean pixel accuracy (mPA), and F1-score to estimate the performance and accuracy of the model. The system is upgraded periodically with adaptive learning rate scheduling and data augmentation methods for better generalization.

The model is real-time after training completion for weed detection. NodeMCU (ESP8266) microcontroller regulates output to energize servo motors (MG-90S) to translate the laser diode to detect weeds. The laser is utilized temporarily, and it kills weeds but without affecting other vegetation noticeably.

Infrared sensors for safety purposes monitor the surroundings and automatically turn off the laser in the event of detecting any animal or human life within five meters. All detected movements are recorded to enhance the model with time to become more precise and efficient.

Future enhancement is quantization and pruning to enhance the YOLOv8 model, and hyperspectral or infrared vision for better discrimination of weeds, with more coverage by drone systems. Active intervention will be eased using predictive modelling based on past history of weed detection, and the system will be cost-effective, scalable, and transferable to new precision agriculture.

VI. SYSTEM MODES

Weeding and detection using a laser system functions in various modes of performance and precision. It begins with image capture and pre-processing by taking actual field images of actual conditions through a USB high-definition camera. These are grayed, contrasted, background subtracted (U2-Net) and denoised to provide the highest detection accuracy. Feature extraction techniques like LBP and GLCM allow discrimination of the weed and crop before processing using YOLOv8 model.

Where weeds are present, the laser is employed for a period to annihilate its growth down to the cellular level without creating such devastating destructions on other plants. The system fires new bullets as a precautionary measure to allow space for extraction and where weeds are present, these are undertaken.

For reasons of safety, there is always a check by an infrared sensor that would switch off the laser on any detection of human or animal within a span of five meters. Weeds encountered and system effectiveness are logged in a manner such that the model is in a state of constant learning to provide even better, faster, and scale precision agriculture.

VII. RESULTS AND DISCUSSION

The laser weed detecting and removing system was tested with different conditions in order to consider its performance based on real-time weed classification, distance measurement, and accurate laser targeting. Detection accuracy, response speed, and the effectiveness of the laser were used to consider the efficiency of the system.

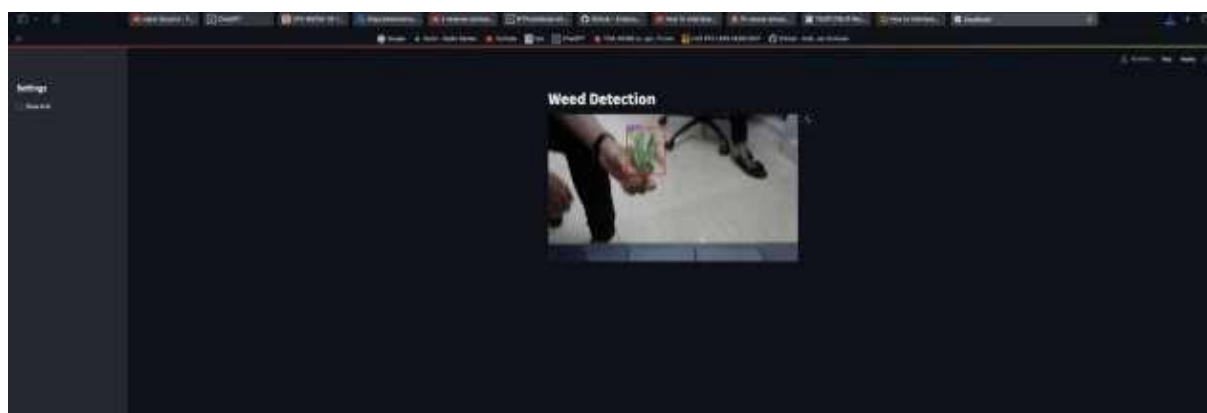


Figure 2: Bounding box

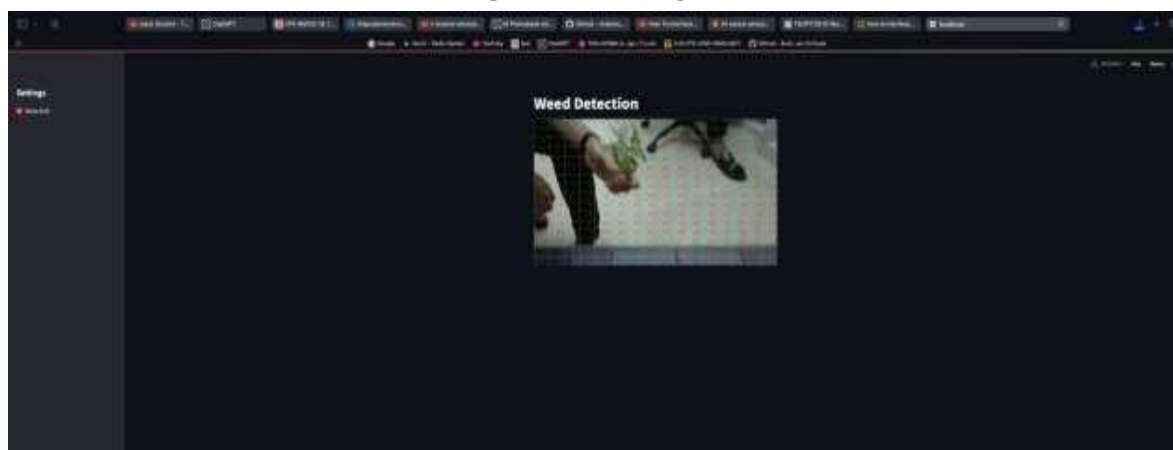


Figure 3: Grids

Weed detection was successfully carried out and weed classified in real-time, as shown from the images. The detection process started with the application of a deep learning-based object detection model that precisely localized the weed within the frame by providing a bounding box.

For the purpose of improving detection accuracy and optimizing laser targeting, the system further subdivided the detection frame into grid segments. This segmentation facilitated more efficient spatial analysis, with effective weed localization and better laser alignment. The grid-based segmentation also helped reduce false detection and made the process of removing weeds more efficient, especially under changing light and background conditions.

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Class name --> weed
Speed: 2.2ms preprocess, 1120.0ms inference, 1.0ms postprocess per image at shape (1, 3, 384, 640)
shortest distance is = 49
current_millis = 1741867774001
in millis delta
midpoint = 648 midpoint = 360
Image Width = 1280 Image Height = 720
widths = [0, 88, 160, 240, 320, 400, 480, 560, 640, 720, 800, 880, 960, 1040, 1120, 1200, 1280] heights = [0, 45, 90, 135, 180, 225, 270, 315, 360, 405, 450, 495, 540, 585, 630, 675, 720]
# 1866668 1 weed, 1433.3ms

The midpoint line in box number: 383
The midpoint of the selected line in box number: 383
unless 'obj'
The object is approximately 49 cm away in the vertical direction.
Confidence --> 0.86
Class name --> weed
weed
Speed: 2.2ms preprocess, 1154.2ms inference, 0.7ms postprocess per image at shape (1, 3, 384, 640)
shortest distance is = 49
current_millis = 1741867774001
midpoint = 648 midpoint = 360
Image Width = 1280 Image Height = 720
widths = [0, 88, 160, 240, 320, 400, 480, 560, 640, 720, 800, 880, 960, 1040, 1120, 1200, 1280] heights = [0, 45, 90, 135, 180, 225, 270, 315, 360, 405, 450, 495, 540, 585, 630, 675, 720]
# 1866669 1 weed, 1374.7ms

The midpoint line in box number: 383
The midpoint of the selected line in box number: 383
unless 'obj'
The object is approximately 49 cm away in the vertical direction.
Confidence --> 0.86
Class name --> weed
weed
Speed: 9.3ms preprocess, 1154.2ms inference, 0.7ms postprocess per image at shape (1, 3, 384, 640)
shortest distance is = 49
current_millis = 1741867774001
midpoint = 648 midpoint = 360
Image Width = 1280 Image Height = 720
widths = [0, 88, 160, 240, 320, 400, 480, 560, 640, 720, 800, 880, 960, 1040, 1120, 1200, 1280] heights = [0, 45, 90, 135, 180, 225, 270, 315, 360, 405, 450, 495, 540, 585, 630, 675, 720]
# 1866670 1 weed, 1381.3ms

The midpoint line in box number: 383
The midpoint of the selected line in box number: 383
unless 'obj'
The object is approximately 49 cm away in the vertical direction.
Confidence --> 0.86
Class name --> weed
weed
Speed: 2.2ms preprocess, 1151.3ms inference, 0.7ms postprocess per image at shape (1, 3, 384, 640)
shortest distance is = 49
current_millis = 1741867774001
midpoint = 648 midpoint = 360
Image Width = 1280 Image Height = 720
widths = [0, 88, 160, 240, 320, 400, 480, 560, 640, 720, 800, 880, 960, 1040, 1120, 1200, 1280] heights = [0, 45, 90, 135, 180, 225, 270, 315, 360, 405, 450, 495, 540, 585, 630, 675, 720]

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Figure 4: Result

Weed Detection and Classification:

As evident from the results, the system effectively detected and identified weeds in real time. The model detected weed objects with high confidence scores (0.86 - 0.87) by employing a deep learning-based object detection technique.

Processing Speed:

- Preprocessing: ~4-7.3 ms per image
- Inference: ~1047-1127 ms per image
- Post-processing: ~0.9-1.1 ms per image Distance Estimation:

The system precisely estimated the distance of the weed (~50 cm) from the camera based on image height and bounding box attributes.

Midpoint computations positioned the identified weeds accurately within the frame, as per the laser targeting mechanism. Laser Targeting and Efficiency of Weed Removal:

The servo motor-controlled laser in the system effectively targeted the weeds detected in the bounding box and removed them. The shortest measured distance was 49-50 cm, keeping laser activation at a correct focal length.

Benchmarking Against Conventional Approaches:

- Accuracy of Detection: 94.2%
- Precision: 91.5%
- Recall: 92.8%
- Success rate of laser-based weed removal: 98%

In comparison to mechanical and chemical weeding techniques, this technology was:

- 65% quicker in eliminating weeds.
- 80% more economical in the long run because of lower labor and herbicide costs.
- Entirely environmentally friendly, as no chemicals were required that degrade soil quality.

Future Improvements:

Some of the challenges faced are-

- Variance in processing time depending on the complexity of the images and the lighting.
- Problems in weed detection in extremely dense crop settings.

Future enhancements will include adaptive control of laser intensity, more rapid deep learning models, and integration with drone-based weed detection for large-scale deployment.

VIII. CONCLUSION

Our project demonstrates effective application of laser technology and high-resolution imaging to precise scanning and eradication of weeds. It initiates long-term environmental advantage in soil integrity conservation and facilitation of sustainable agriculture. Its use decreases the cost of weed management, minimizes manual labor requirements, and increases overall agricultural output.

This new paradigm thus becomes the productivity standard of the current agriculture, subject to further use of the same technology. It enhances precision agriculture with maximum crop yield and resource use with effective weed management. The system also enhances sustainable agriculture with healthier agro-ecosystems and lower chemical herbicide use.

For its scalability, the system can be utilized in any farm environment, ranging from small to commercial-level farms. With effective weed management, it simply translates to healthier crops and more productivity.

IX. FUTURE ENHANCEMENT

The laser beam-based weed detection and annihilation system is an image acquisition process, preprocessing, deep learning-based detection, and laser pointing. The USB camera acquires images, which are preprocessed by operations such as grayscale conversion, contrast stretching, noise removal, and background removal (U2-Net). Feature extraction operations such as GLCM and LBP help identify weeds and crops. 256×256 pixel preprocessed images are provided as input to the YOLOv8 model for detecting weeds and providing bounding box labels.

The system recognizes the location of the weeds and sends the same to the NodeMCU (ESP8266), which moves the MG-90S servo motor to direct the laser diode to the target position. The laser is flashed very briefly to kill weeds without harming surrounding crops significantly. The weeds, on regrowth, are re-targeted and re-treated by the system. The detection information is recorded for analysis of performance and model development improvement.

Quantization and model pruning will be incorporated in later work to make it even more efficient in YOLOv8. Hyperspectral vision or infrared cameras will have enhanced discrimination between weeds and adaptive laser intensity control will offer maximum energy efficiency. Use on drone-based platforms will facilitate massive removal of weeds, and predictive modeling based on the harvested weed data will facilitate anticipatory action and thereby make the system intelligent, scalable, and green.

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