Steering Control of Ackermann Architecture Weed Managing Mobile Robot

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A robot designed to identify and remove weeds from crops is known as a weed control robot. Weeds compete with primary crops for moisture, hinder their growth, and may harm both human and animal health, leading to reduced crop yields. Traditionally, herbicides and other chemicals have been used to eliminate weeds, but these methods can damage crops and pollute the environment. In this work, we propose a new semantic weed detection method based on the PC/BC-DIM network, which demonstrates superior performance and classification accuracy compared to existing approaches. We developed an autonomous weed control robot incorporating Ackermann Architecture and a delta robot. The delta robot is equipped with a camera at its base to detect weeds in real-time. First, the robot captures images using the camera, and through image processing techniques, it differentiates weeds from crops. Detected weeds are then eliminated using an electrical discharge method, where electrodes attached to the robot's end effector burn the targeted weeds. Additionally, we developed a path-planning and obstacle-avoidance system to help the mobile robot navigate the field. This system uses stereo vision to capture stereo images of the environment and calculate their disparity. By extracting depth information, the robot can detect obstacles, avoid them, and follow the shortest path using the A* algorithm. The results from this work are simulation-based, demonstrating effective weed detection in field images and efficient robot navigation using stereo images. The system achieved an overall accuracy of 81.25%. Although the system performs moderately well, the relatively high False Positive Rate and Root Mean Square (RMS) Error indicate the need for further improvements to reduce errors and false positives.
Future work will focus on enhancing weed removal and implementing the simulated results on hardware.

Keywords: Ackermann Steering, Weed Detection, Mobile Robots, Path Planning, Stereo Vision, Image Processing.

Introduction:

A robot designed to identify and eliminate weeds from crops is known as a weed control robot. Weeds are unwanted plants that compete with crops for nutrients, moisture, and space, which hinders crop growth and reduces yields. They can also harm human and animal health, contributing to significant crop losses [1]. Due to these negative impacts, farmers must remove weeds, a task that is both time-consuming and labor-intensive. For many years, herbicides and chemicals have been used to eliminate weeds, but these substances can harm crops and pollute the environment. To speed up farming operations and reduce manual labor, farmers often use equipment such as tractors, weeders, and harvesters. While some farmers can afford such machinery, others cannot, especially since these machines require expensive fuel and contribute to environmental pollution. For these reasons, relying solely on heavy equipment may not be the best solution [2]. Farmers also use fertilizer sprayers to boost crop growth and yield, but this process requires time and effort. To address these challenges, robotic weed control offers a promising solution by preventing weeds from disrupting crops and improving farming efficiency.

Many weed control robots can perform tasks like electrical discharge, mechanical weeding (using hoe tools), and targeted chemical spraying [3]. This project will focus on the electrical discharge method, which can eliminate weeds in two ways: continuous contact and spark discharge. The first method uses short bursts of high-voltage electricity to kill weeds, speed up fruit ripening, and thin plant growth. The second method delivers energy in brief pulses (e.g., one microsecond) using two electrodes positioned on opposite sides of the plant. This pulse thins plant rows, kills weeds, cuts plant sections, and dries out the leaves of root crops. The plant tissue is damaged either by the sudden electrical surge or the heat generated by the electricity.

This project will also implement Ackermann architecture, which is based on a four-wheel independent steering system. It includes several steering modes:

- **Ackermann steering:** Allows the inner and outer wheels to rotate at different radii.
- **Active front and rear steering:** Turns the front wheels in the opposite direction of the rear wheels.
- **Crab steering:** Moves all wheels in the same direction to allow diagonal movement.
- **Spinning:** Rotates the vehicle around a central point.

This system allows the robot to switch between steering modes depending on the situation, making movement more efficient. The Ackermann steering structure solves the issue of different steering angles caused by varying radii of the left and right wheels. According to Ackermann's steering geometry [4], by adjusting the crank of the four-link structure, the robot can increase the inner wheel's steering angle by 2-4° more than the outer wheel when turning along a curve. This adjustment helps position the robot's steering center, allowing smooth turns by aligning the four-wheel paths with the rear axle's extension line.

Ackermann steering is known for supporting high payloads and improving movement efficiency. It is commonly used in cars, although the structure tends to be too large for narrow spaces. This project will enhance the robot's functionality using image processing and machine vision techniques. Cameras installed on the robot will capture images of the farmland. These images will be processed using algorithms that identify weeds based on their unique characteristics. Additionally, a stereo camera will capture images from two angles to analyze the environment, detect free spaces, plan the robot's path, and guide its movement.

Once weeds are detected, the robot's control system will instruct its mechanical arm or tool to remove them from the ground. A previous group worked on an autonomous weed control robot but left several limitations:

1. The robot detected weeds in a virtual environment rather than a real one.
2. A weed removal mechanism was not developed.

3. There was no navigation system for the mobile robot.
The main aims of this research are:

- To develop a system that can distinguish between weeds and crops in cotton fields using image processing techniques.
- To build a system for weed removal in cotton fields using electrical discharge.
- To create a navigation mechanism for the weed control mobile robot.

Literature Review:

The development of autonomous agricultural robots for weed management has gained significant attention in recent years, particularly as a means to reduce chemical herbicide dependence and enhance precision farming efficiency. Traditional weed control methods rely heavily on manual labor or herbicide spraying, both of which present economic and environmental drawbacks [1]. Autonomous robotic systems equipped with computer vision, deep learning, and mechanical weed removal mechanisms offer a sustainable alternative, allowing for precise identification and targeted elimination of weeds without harming crops. This literature review explores previous advancements in weed detection, robotic navigation, and path planning to establish the significance of the proposed study.

With precision farming, autonomous robotic weeding systems have proven to be effective in reducing the use of agrochemicals like pesticides and herbicides. A study [5] proposes a multi-camera, non-overlapping approach to enhance the weed control system's flexibility in managing unknown classification delays. Consequently, an advanced weed-control technique [6]becomes necessary. In this approach, images of plantation rows are captured at regular intervals using image processing methods.

In [7], the author developed a low-cost delta robot arm equipped with a vision system, capable of gripping objects of various sizes. This economical design uses stepper motors instead of AC servo motors. In [1], an autonomous agricultural mobile robot for outdoor mechanical weed control is introduced. This robot operates with two vision systems: a color-based system to distinguish between weeds and crops, and a gray-level system to detect the row structure created by crops, guiding the robot along the rows. In [8], Kulkarni et al. designed a robotic vehicle with four wheels, steered by a DC motor and equipped with an IR sensor system to manage weed growth in fields. In [9], the authors developed a new technology for weed control called "crop signaling." This method enables plants and weeds to be machine-readable, allowing them to be automatically distinguished based on their unique features.

The effectiveness of robotic weed management heavily relies on accurate weed classification using image processing and machine learning techniques. Early studies employed handcrafted feature extraction methods, such as color thresholding and edge detection, to differentiate between crops and weeds. However, these methods were often limited by variations in lighting, soil conditions, and plant morphology. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs) and Transformer-based architectures, have significantly improved weed detection accuracy. Most modern approaches rely on pre-trained deep learning models (e.g., ResNet, YOLO, EfficientNet) trained on large-scale agricultural datasets for real-time weed identification (Lin et al., 2023) [4] . However, deep learning models require high computational power and extensive datasets, which may limit their usability in field-deployable robots with constrained hardware. This study explores Predictive Coding-Biased Competitive Divisive Input Modulation (PC/BC-DIM) neural networks for weed classification, a less common approach in precision agriculture. While previous studies have demonstrated the effectiveness of CNNs in weed classification, the proposed study seeks to evaluate whether PC/BC-DIM can offer a computationally efficient alternative while maintaining high classification accuracy.

In this study, we present an autonomous weed control mobile robot that integrates Ackermann steering architecture with Delta robot-based weed removal. Unlike previous approaches, our system uses real-time stereo vision-based disparity mapping, followed by A* algorithm-based path planning for effective obstacle avoidance. Additionally, a PC/BC-DIM neural network is employed to enhance the accuracy of weed detection. The proposed system achieves an accuracy rate of 81.25%, making it a promising solution for precision agriculture. This work bridges the gap between simulation-based weed classification and real-world navigation, paving the way for autonomous and efficient weed management.

Material and Methods:

Weed detection using an autonomous mobile robot is a complex challenge. This study focuses on designing a system for weed detection and removal in agricultural fields. The project leverages computer vision techniques, including image processing, to achieve this goal. The mobile robot is equipped with two cameras: one dedicated to weed detection through specialized image processing, and a stereo camera that facilitates efficient path planning.

The Delta robot, mounted on the Ackermann architecture of the mobile robot, navigates through the field and removes weeds after detection using an electrical discharge technique via electrodes attached to its end-effector. The system's overall functionality is illustrated in the block diagram shown in Figure 1.

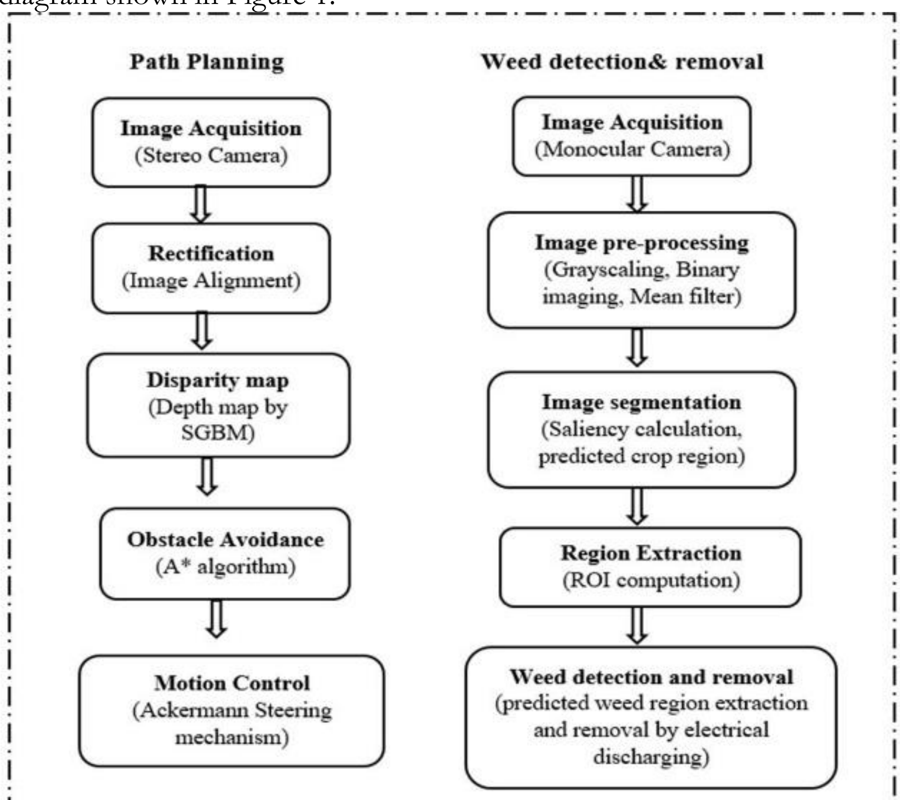

Figure 1. Block diagram of weed control robot

Path Planning:

Path planning for robot navigation follows several key steps. The process starts by capturing stereo images of the environment using a stereo camera. After capturing, the images are rectified to align both on a common plane. A disparity map is then created, showing the difference in the object's position between the two images. This is followed by calculating the depth map using the SGBM algorithm. Based on the depth map, the robot detects and avoids obstacles and plans a clear path using the A* algorithm. Finally, motion control based on an Ackermann steering architecture helps the robot follow the planned path accurately.

A stereo camera setup is placed at the front to capture images for navigation. It takes two images of the same scene from slightly different angles, mimicking human binocular vision. These images are processed further. Image rectification simplifies the matching process by aligning corresponding points along the same row. First, camera calibration parameters (intrinsic and extrinsic) are calculated. Using these parameters, geometric transformations adjust the images so that corresponding points in both images align horizontally. For example, if a tree appears slightly to the right in the left image and slightly to the left in the right image, rectification aligns the tree in both images on the same horizontal axis.

The disparity map shows the difference in the object's location between the left and right images. Each color in the disparity map represents how near or far an object is—the brighter areas indicate closer objects, while darker areas show objects farther away. The depth map is calculated using the Semi-Global Block Matching (SGBM) algorithm. This algorithm compares small pixel blocks in one image with corresponding blocks in the other image to find the best match by trying different disparities. Small disparities indicate close matches, while large disparities show mismatches.

Path planning and obstacle avoidance are done using the A* algorithm and an occupancy grid based on the depth map. The grid represents obstacles as occupied cells and open space as unoccupied cells. A path from the starting point to the target position is generated using the A* algorithm, which finds the best route by minimizing both the current travel cost and the estimated remaining cost. Additionally, points from the depth map are transformed into a 3D point cloud and projected back onto the 2D image to visualize and detect obstacles. Motion control ensures the robot moves along the designated path. This robot uses the Ackermann steering design, which controls vehicles with differential steering, such as wheeled robots. It calculates precise steering angles and velocities, helping the robot remain stable and maneuverable. The steering angles are determined using depth map data to guide how much the robot should turn to follow the planned path, considering the vehicle's geometry and point coordinates.

Weed Detection:

The semantic weed detection method used in this project is based on our earlier work [10]. The process starts with capturing an image using a secondary camera mounted on the base of a delta robot, above its end effector. This image is then used for further processing to detect weeds. The input image is first converted to grayscale to simplify processing. Next, the grayscale image is converted into a binary image by applying an optimal threshold value, which minimizes the variance between background and foreground (crop-weed areas). Pixels are classified as either background or crop-weed regions. To reduce noise, small objects are removed from the binary image, and a mean filter is applied to smooth the image by averaging pixel values in a specific window size. This filtering highlights the regions of interest and enhances image clarity.

Image segmentation is the next step, dividing the digital image into segments or pixel sets to make the image easier to analyze. Segmentation helps identify objects and boundaries (e.g., lines and curves) within the image. In this case, segmentation labels each pixel to group those with similar attributes.

The segmentation process starts by generating a saliency map using different algorithms. The saliency map highlights key areas that stand out from the background, such as weed regions. An error map is also computed to assess segmentation accuracy. Several saliency maps are generated, combined, and refined to create a comprehensive map that highlights the most important areas (i.e., weeds). A PC/BC-DIM neural network (Predictive Coding-Biased Competitive Divisive Input Modulation) and Gabor filters are used to calculate the saliency map. The PC/BC-DIM network mimics how the human brain processes visual images and consists of three types of neurons:

1. **Reconstruction Neurons (R)**: These neurons use prior information to reconstruct the input image, acting as filters by calculating their activity using synaptic weights.

2. **Error Neurons (E)**: These neurons compute the difference between the original input image and the reconstructed image. A large error suggests that the reconstruction is inaccurate. Element-wise division is used to calculate the error and improve accuracy.

3. **Prediction Neurons (Y)**: These neurons adjust their predictions based on the error data, updating their activity to improve the image reconstruction.

The network generates feature maps by applying Gabor filters at different phases and orientations to capture distinct image features. Through iterative reconstruction and prediction, the network produces a refined saliency map that emphasizes key image areas. The saliency values from the final map help distinguish crops from the background, and a predicted crop region is extracted from the binary image. This predicted crop region is then subtracted from the extracted region of interest (ROI) to isolate the weed region. Finally, the detected weed region is compared with ground truth images to evaluate detection accuracy.

$$g(\sigma,\lambda,\phi,\theta) = \exp\left\{-\frac{\hat{x}^2+2\hat{y}^2}{2\sigma^2}\right\}\left[\cos\left\{\frac{2\pi\hat{y}}{\lambda}+\phi\right\}-\cos(\phi)\exp\left\{-\left(\frac{\pi\sigma}{\lambda}\right)^2\right\}\right] \quad (1)$$

The predicted crop region is labeled in green to make it easily identifiable. The primary objective of feature extraction is to detect and analyze the key areas of the image. This involves isolating the region of interest (ROI), which includes the parts of the image containing crops and weeds while eliminating the background. In the next step, the predicted crop region is subtracted from the ROI image (containing both crops and weeds) to isolate the predicted weed region. The extracted weed region is then labeled for easy visualization, with the weed region highlighted in red. Finally, the labeled predicted crop and weed regions are combined to display the detected weed region, as shown in the results section.

To evaluate the accuracy of weed detection, statistical measures and error calculations are performed by comparing the predicted images with the ground truth images. The term "ground truth" refers to data collected directly from the field, which is essential for verifying image data against actual ground-based characteristics and conditions.

Results and Discussion:

Path Planning Results:

The input image was captured using stereo cameras, as shown in Figure 2. This image includes the left and right stereo views of the garden and ground.

Figure 2. Stereo input images

Figure 3. Rectified stereo input images

Secondly, the rectification of the image mentioned above is performed, as shown in Figure 3. Disparity, which measures the difference in the object's position between the left and right images, is calculated and displayed in Figure 4.

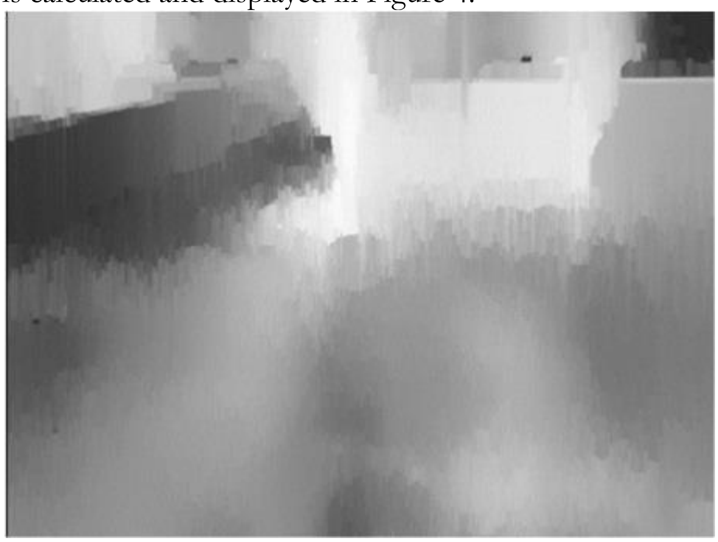

Figure 4. Disparity map

In Figure 5, the robot detects the tree as an obstacle in its path. The colorful line represents the path planned by the robot to avoid the obstacle and navigate through the garden using the A* algorithm.

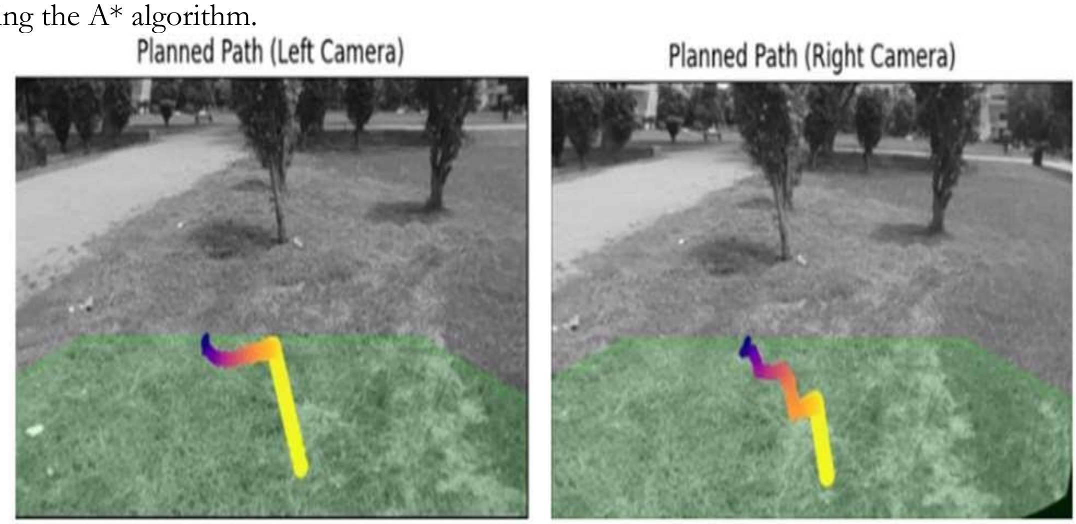

Figure 5. Planned path

Weed Detection Results:

The image captured by the secondary camera is used as the input image, which is then converted to grayscale, as shown in Figure 6.

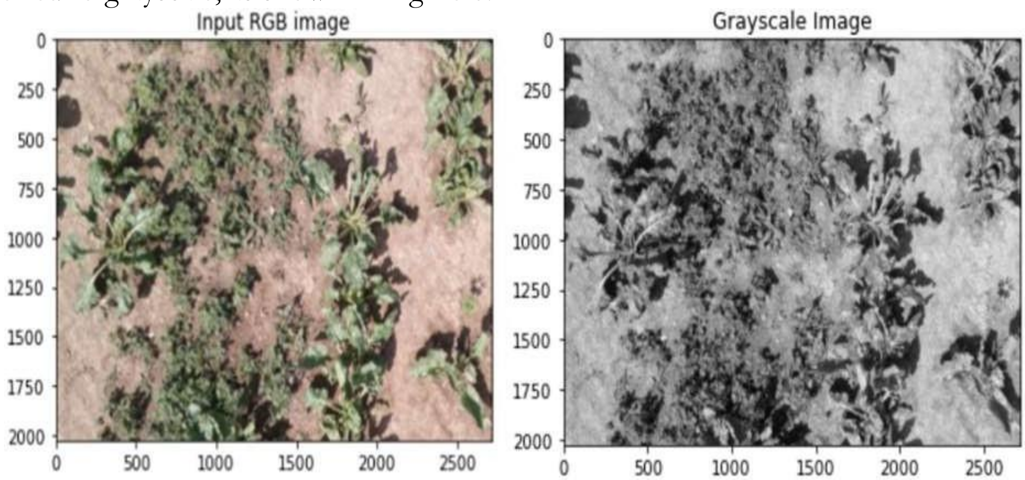

Figure 6. Input and grayscale image

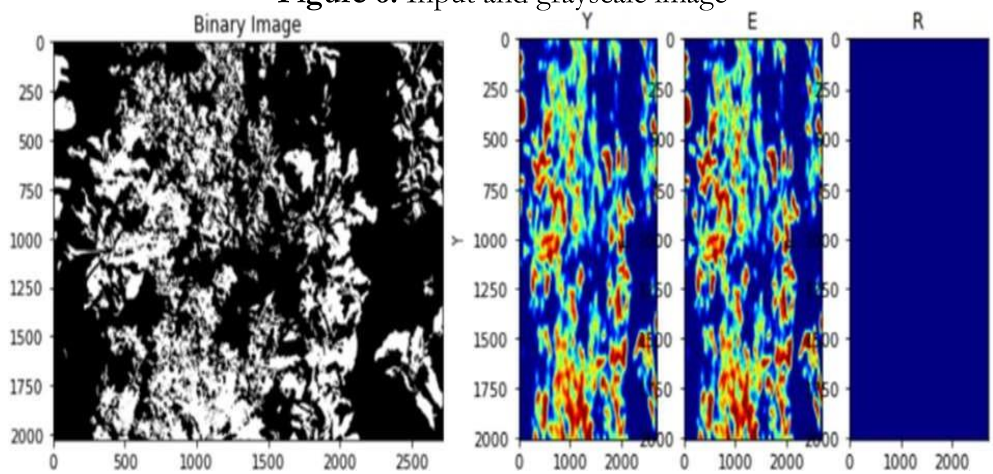

Figure 7. Binary image and saliency map

The grayscale image is then converted into a binary image. In the next step, the saliency map and error map are calculated to highlight the weed region, as shown in Figure 7. Using the saliency maps, the predicted crop region is extracted from the binary image. Once the crop region is detected, it is labeled in green, as shown in Figure 8.

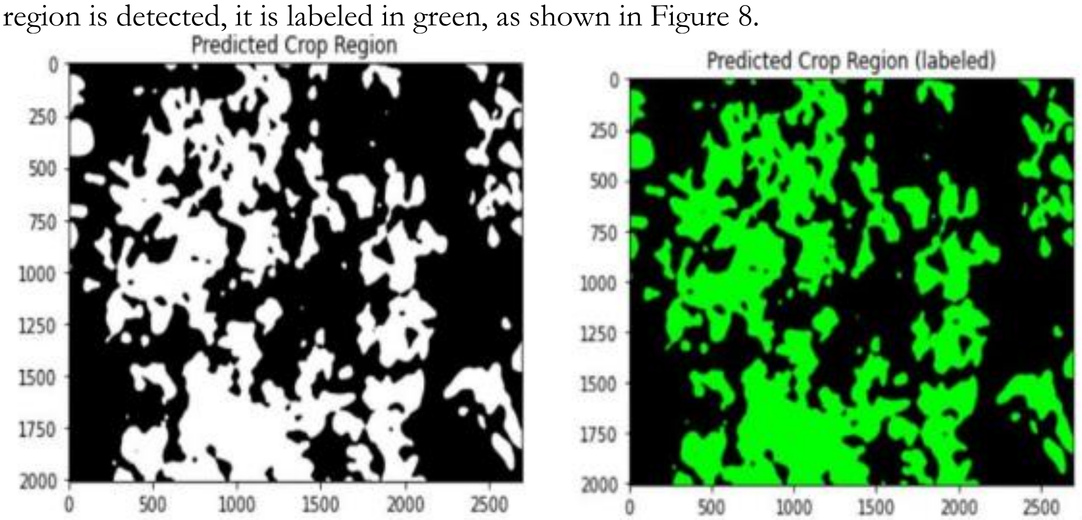

Figure 8. Predicted crop and labelled

In the next step, the ROI (Region of Interest) is extracted from the input RGB image. The predicted crop region is then subtracted from the crop-weed image to separate the weeds from the crops, as shown in Figure 9.

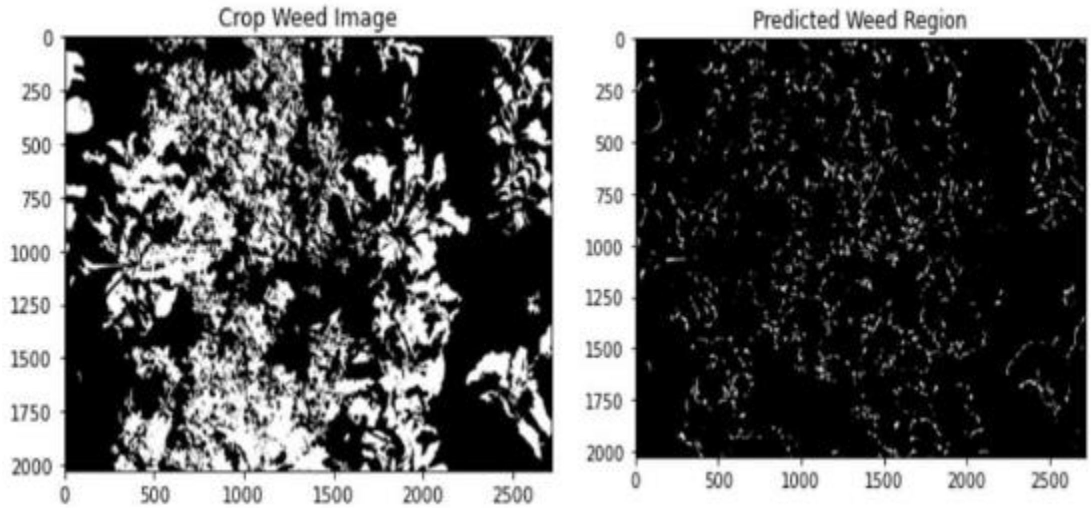

Figure 9. Predicted crop and labelled

After detecting the weed region, it is labeled in red to highlight the extracted area. Both the crop and weed regions are then combined to clearly differentiate between them. The results are shown in Figure 10. The errors are calculated by comparing the predicted image with the ground truth (GT) image, as shown in Figure 11.

The calculations of the false positive rate (FPR) and true negative rate (TNR) help to understand the trade-off between sensitivity (the ability to detect weeds accurately) and specificity (the ability to correctly identify non-weeds).

Three types of errors are computed:

1. **Type 1 (False Positives)**: Non-weeds are incorrectly detected as weeds.
2. **Type 2 (False Negatives)**: Weeds are overlooked or not detected.
3. **Type 3 (Total Error)**: The combined error, accounting for both false positives and false negatives.

The efficacy of the weed detection model is demonstrated in Figure 12.

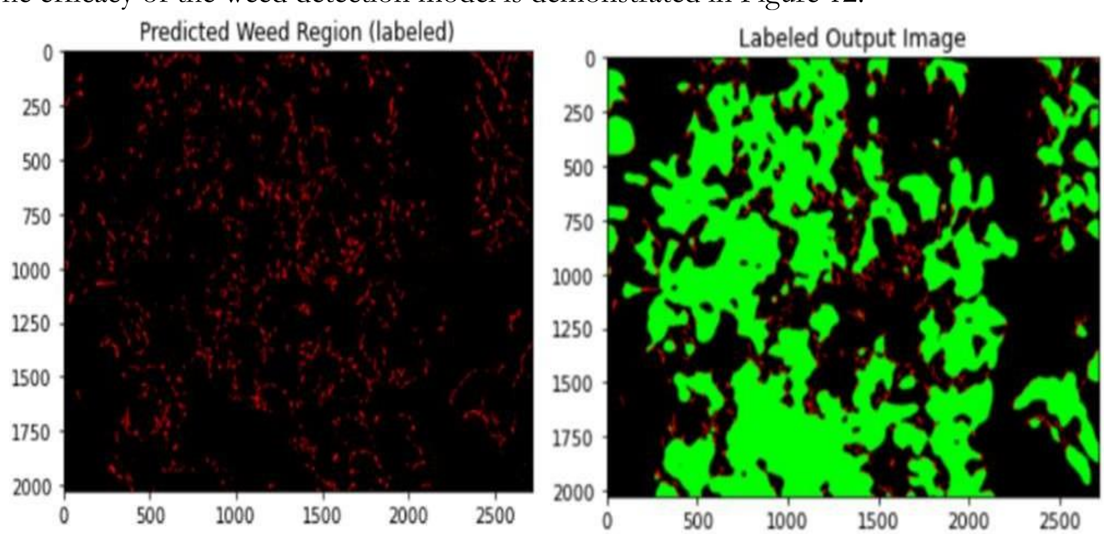

Figure 10. Predicted weed region and labelled

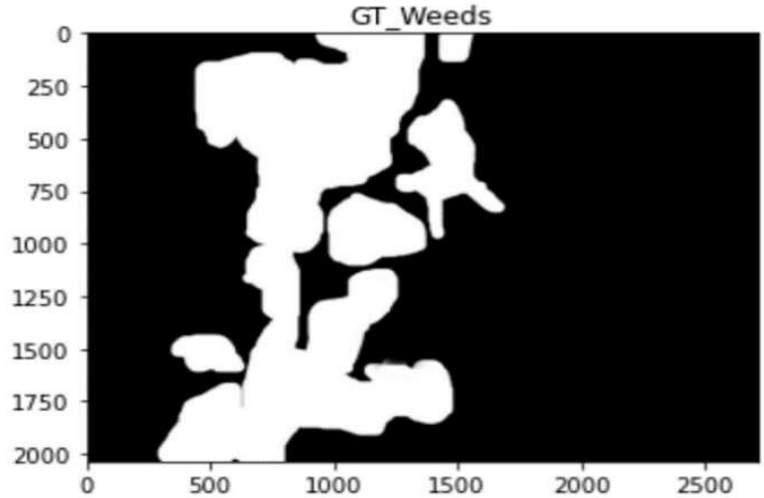

Figure 11. Ground truth weed image

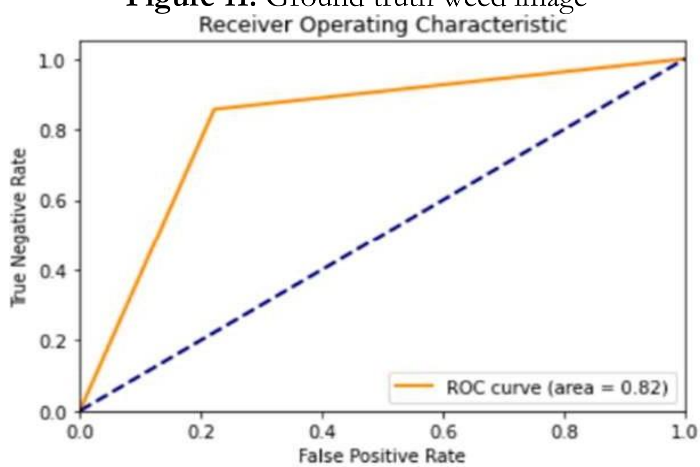

Figure 12. ROC curve

The accuracy analysis of the weed detection model is presented in Table 1.

Table 1. Accuracy analysis

Error	%
Type 1	22.22
Type 2	14.2857
Mean error overall	18.75
Mean accuracy overall	81.25
RMS error	43.30
Mean square error overall	18.75
False positive rate	0.22
True negative rate	0.77

The results show the percentage accuracy and classification errors for weed detection. In cases of dense vegetation, misclassifications are more likely to occur because weeds and crops may overlap, making it harder to distinguish between them and leading to higher error rates.

Discussion:

The primary objective of this research was to design a weed detection mechanism in real-world environments and enable the robot to navigate fields while avoiding obstacles. Various techniques exist for robot navigation, including machine learning methods like Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Artificial Neural Networks (ANN), and Region-based Convolutional Neural Networks (RCNN). Although these approaches are effective in detecting objects in a given environment, we opted for the A* algorithm due to its robustness and efficiency in path planning.

Additionally, there are recent advancements in navigation based on LIDAR data, Monocular Vision, and Stereo Vision. Each of these methods has its advantages and limitations. For example, LIDAR offers accurate detection but is costly and has a limited perception range, while Monocular Vision may not guarantee reliable accuracy. For weed detection, we employed an image-processing technique that effectively works in natural environments. This method involves several steps: image pre-processing, image segmentation, and feature extraction. By integrating the information obtained from these steps, we successfully enhanced the detection and classification of weeds.

One of the key advantages of this study is the integration of stereo vision with the A path planning algorithm*, enabling the mobile robot to navigate agricultural fields with higher accuracy and adaptability. Unlike conventional GPS-based navigation, which may struggle with occlusions caused by dense vegetation, stereo vision allows for real-time depth perception and object avoidance. Previous research (Lin et al., 2023) has demonstrated that vision-based navigation improves localization accuracy in unstructured environments, making it a suitable approach for row-crop farming applications. However, the computational demands of real-time stereo vision processing remain a challenge. Future work should explore edge AI processing techniques to reduce latency and optimize real-time decision-making in embedded robotic systems.

Furthermore, while this study successfully employs PC/BC-DIM neural networks for weed classification, additional comparisons with CNNs and Transformer-based models would provide a more comprehensive analysis of model efficiency and accuracy. Prior research (Naveed et al., 2023) [10] indicates that pre-trained deep learning models such as YOLOv5 and EfficientNet achieve state-of-the-art weed detection performance, suggesting that a hybrid approach combining PC/BC-DIM with CNN-based feature extraction could enhance classification robustness. Additionally, incorporating data augmentation techniques could help address dataset limitations and improve model generalization across diverse agricultural conditions.

Finally, the electrical discharge-based weed removal mechanism presents a promising alternative to conventional mechanical or chemical-based weeding methods, but its long-term energy efficiency, operational safety, and impact on soil health require further evaluation. While previous studies (Diprose et al., 1984) [3] suggest that high-voltage weed removal is effective in disrupting plant cellular structure, excessive energy consumption may limit scalability in large farming applications. Future research should investigate energy-efficient discharge optimization techniques and evaluate potential side effects on surrounding crops, soil microorganisms, and long-term field productivity. Additionally, exploring hybrid weed removal methods, such as combining electrical discharge with robotic precision cutting or thermal weeding, could further improve the system's effectiveness and sustainability in precision agriculture.

Conclusion:

We discussed the primary objective of our project, which is to design the steering control for an Ackermann architecture-based weed-managing mobile robot. To achieve this, we developed a system capable of detecting weeds in real-world environments and navigating the robot while avoiding obstacles. We also outlined the methodology used to implement the project. In the first stage, we focused on path planning by capturing stereo images of the environment and rectifying them. Next, we calculated the depth map using the SGBM algorithm. With the help of the A* algorithm, the robot was then able to navigate the field while avoiding obstacles.

In the second stage, we addressed the weed detection task. For this, we first captured images using a secondary camera mounted on the base of the delta robot, positioned above its end effector. The captured image was then processed to detect weeds. This process involved converting the image to grayscale and then to a binary format by applying a threshold to emphasize key regions while minimizing the background. From the binary image, the crop region was identified using a saliency map and ROI (Region of Interest), which highlighted the crop area. The weeds were then detected by subtracting the identified crop region from the thresholder image. In the future, extensive field testing and validation will be conducted to assess how the dynamic field environment affects the performance of the proposed approach.

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