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Development and Experimental Analysis of a Robotic System for Automated Vegetable Planting Utilizing Precision Agriculture and Computer Vision

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Abstract

This work presents the development of a precision agriculture robot capable of managing vegetable, berry, and legume patches within a vegetable crop. It utilizes computer vision, Internet of Things (Iot) cloud-based processing, which, through an online webapp a digital twin coordinates planting activities such as sowing, weed control, and watering in a real vegetable crop raised bed where the physical robot is installed. An analysis of the computer vision methods for automatic weed detection under different conditions and foreign bodies is presented. According to experimental results, by the experiment scenarios, some computational theoretical improvements are proposed in order to reduce false detection of weeds such foreign bodies in the raised crop bed.

Keywords

Precision agriculture, computer vision, IoT, cloud computing, digital twin, Farmbot, efficient consumption.

1. Introduction

The issue of food security is a complex problem there affecting billions of people worldwide. Producing enough food to meet global demand is an increasing challenge, exacerbated by several factors like climate changes, rainfall patterns change, rising temperatures and other factors around the world. These changes can reduce the availability of fresh water, essential for agriculture, and negatively impact soil health.

Furthermore, agricultural expansion often leads to deforestation and biodiversity loss, compromising the ecosystems that support food production. The intensive use of fertilizers and pesticides, in turn, can pollute soils and water bodies, affecting human and environmental health. Growing urbanization also puts pressure on agricultural lands, reducing the space available for cultivation.

Increase productivity and reducing the costs involved in the process can be achieved by minimizing waste in seeding and watering processes, and preventing the growth of weeds within the crop fields. Weeds act like parasites, consuming the water and nutrients that are intended for the cultivated plants nearby.

A prime example is the rational use of inputs facilitated by precision agriculture technologies. The rational use of inputs for cultivation is a critical element in reducing production costs and preserving natural resources, such as water. Agriculture accounts for approximately 70% of the world's freshwater consumption[1]. Consequently, water management is very important and must be executed efficiently.

Therefore, to maintain and enhance food production levels, agriculture is increasingly expanding its research into new planting technologies. One significant area is precision agriculture robotics, which helps mitigate challenges such as population growth, the scarcity of qualified labor in agronomy, and accelerated urbanization. By automating common labor tasks such as land preparation, sowing, and pest control, these robotic technologies reduce the reliance on human labor and increase efficiency, ensuring more sustainable agricultural practices [2].

Many projects involve navigating robots across open-area crops using various types of travel mechanisms, such as wheels, track-type, or even leg-type. Each of these has a specific and complex algorithm, usually a complex system, with expensive hardware and various sensors like inertial units, gyroscopes, accelerometers, ultrasonic devices, lidar, and others, all to determine the robot's relative position and navigate through the open fields [3].

Image processing is a crucial component utilized by computer vision systems in precision agriculture. Through the acquisition of images using a camera, these images are then processed by computer to extract and classify information, such as the detection of diseases in plants, crops, or fruits. Weed detection, for example, can help reduce the consumption of herbicides and fresh water, not only because weeds consume water to grow, but also because herbicides need to be mixed with fresh water. These technologies help farmers to detect problems early and apply targeted interventions, enhancing yield and reducing waste [4].

In [5] is proposed a method aimed to determine weed density by calculating the ratio of pixels identified as weeds to the total number of pixels in a given crop area. This methodology allows the precise mapping and distribution of weeds within crop fields. Such precision enables targeted management practices, including the application of herbicides specifically to areas affected by weeds [6]. By focusing treatments only where needed, this approach significantly reduces disturbances to soil and plants, thereby decreasing the costs associated with pesticide use and water consumption, and enhancing overall agricultural sustainability.

Another relevant point is the sensing of soil moisture and other environmental parameters, such as temperature, humidity, and CO2 levels. In this field, IoT technologies area attractive, utilizing sensors information for an intelligent decision-making system [7, 8] . From IoT data, agricultural systems can significantly enhance water efficiency. This integration of technology facilitates precise control over irrigation, ensuring that water resources are utilized optimally and sustainably [9, 10] .

Launched in 2016 by a team of engineers at a California-based startup, Farmbot represents an innovative technology that utilizes advanced computer vision algorithms for precise planting. This system is designed to automate the planting process of leguminous vegetables, root vegetables, and low-growing fruits, significantly enhancing productivity. Farmbot is highly scalable, making it suitable for various planting areas ranging from small garden beds to extensive plots of land and greenhouses. This scalability helps in conserving water, reducing labor costs, and optimizing the use of other vital resources [11, 12]. In the past, researchers and students around the world successfully implemented FarmBot-based platforms, utilizing the provided open-source documentation [13].

This paper describes the development and experimental performance analysis of a FarmBot-based robot equipped with capabilities for planting, watering, and weed detection. By experimenting scenarios that introduce foreign bodies into the crop and alter the native configuration parameters, this study evaluates the effectiveness of the existing computer vision algorithms used in the Weed Detection System (WDS). It proposes several enhancements to be implemented in parallel processes, with the Weed Detection Algorithm (WDA) as the central process.

A major area identified for theoretical improvement is the robots ability to distinguish between foreign bodies and real weeds feature that is currently lacking in the robots WDA. For this study, any modifications are made to the original source code of the software. The only change was to the color spectrum parameter of the WDA, which was altered for different experiment scenarios.

Additionally, the hardware has been upgraded by replacing the original fixed-focus borescope camera, as described in the documentation, with an autofocus version to enhance weed identification. By addressing these issues, the study aims to improve the accuracy and functionality of the WDS.

2. The developed robotic system

This section outlines the electronic and electromechanical components integrated into the developed system. The system has the capability to monitor soil moisture, eradicate weeds around the plants, and automate seed sowing. The robot navigates using X, Y, and Z coordinates provided by the user through a digital twin interface, accessible via a cloud-based internet platform. Figure 1 presents the robot from an oblique perspective, mounted on the vegetable crop raised bed.

Figure 1. Developed robotic system

The main robot's components are shown in Figure 2. The Z-axis arm moves through a gantry on the Y-axis, which runs on rails along the vegetable patch on the X-axis. A set of tools can be attached to the arm support, such as seed planting tips, watering cans, weed killers, and soil sensors.

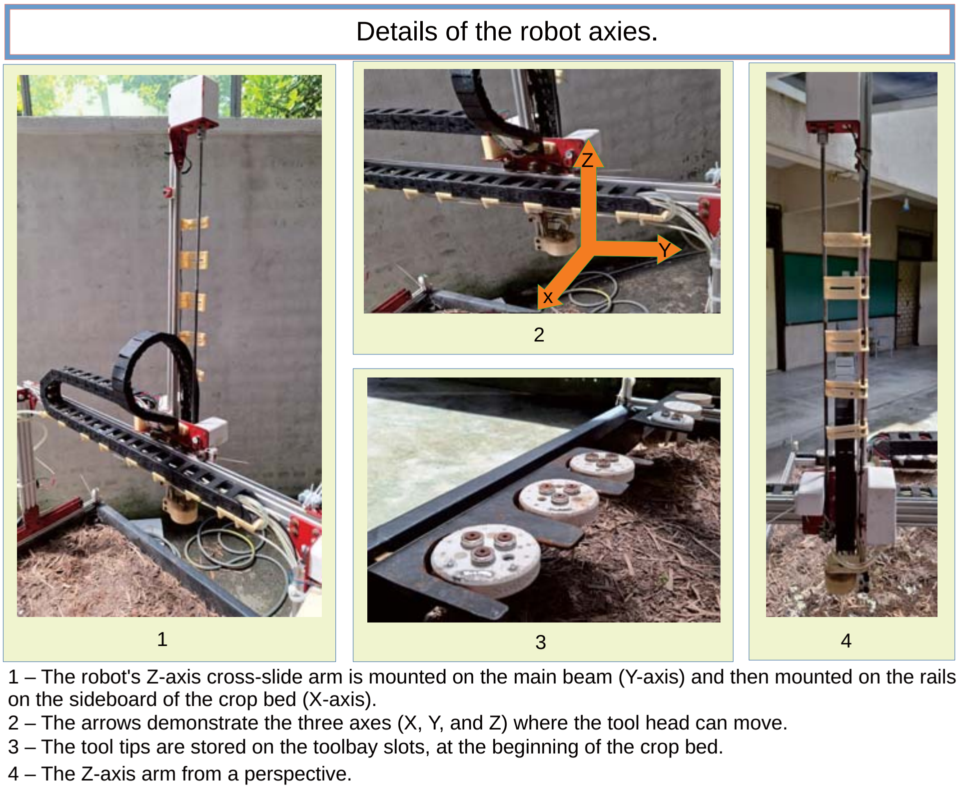


Figure 2. Main components of the developed robotic system.

This type of movement offers several advantages for managing small to medium-sized garden beds, including reducing complexity and cost-effective implementation.

2.1. Details of the electronics mount

A block diagram of the system components is presented in Figure 3. An Arduino board is used as the robot's motherboard aimed to control the motors and read sensors. To reduce costs and further simplify the system, end-of-travel sensors were used instead of encoders.

It is equipped with a 1.4 Ramps shield and four stepper motors drivers. A 250W 12Vdc power supply provides sufficient power for the electronics, motors, and peripherals such as the vacuum pump and a solenoid valve. Both of these peripherals utilize a DC booster converter to increase the voltage to 24V DC.

A Raspberry Pi, with a Linux-based software image installed on the microSD card, manages communication with the digital twin on the internet, transmitting commands to the motors and peripherals. The Raspberry Pi and Arduino Mega board are connected via a USB interface. The Raspberry Pi is powered directly through GPIO pins 4 and 6 with 5 Vdc, supplied by the DC buck converter directly from the power supply, while the Arduino is powered with 12Vdc connected to the Ramps shield directly from the power supply. A borescope camera used to acquire images and the processing is made through the Raspberry Pi.

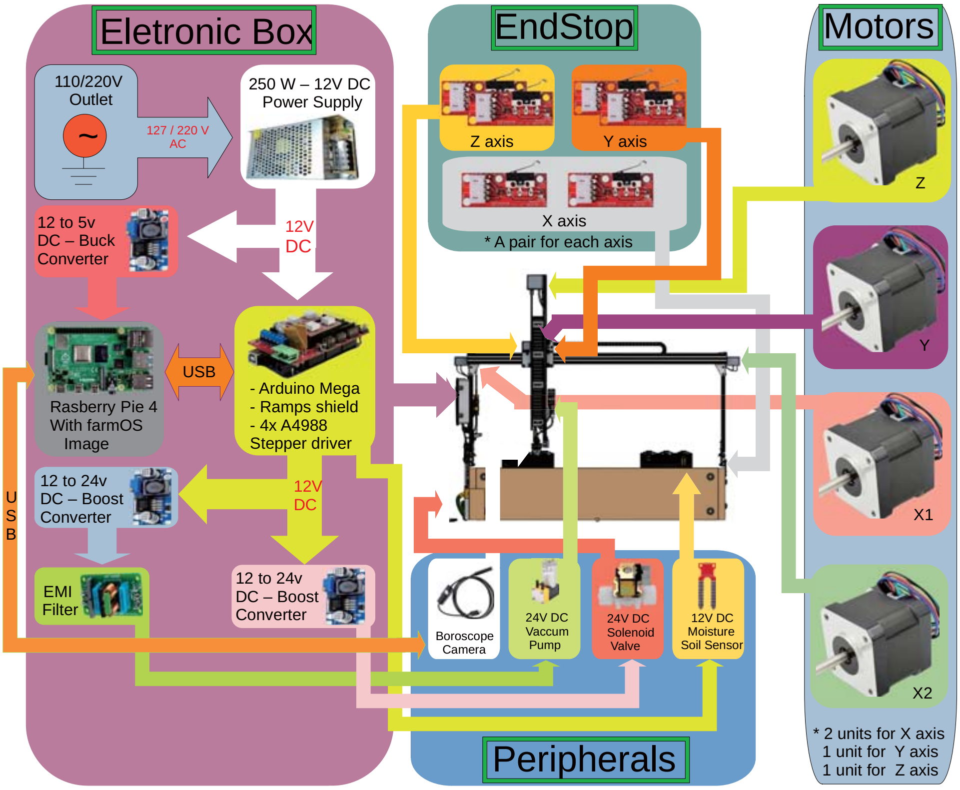


Figure 3. Electronic connections map the robot's location.

2.2. Web user interface and system communication tecnhology

The Creative Commons license CC0 (for equipment and documentation) and the Massachusetts Institute of Technology MIT license (for the program) allow the project to be used free of charge and subject to modification (Open Source) by the user, without the prior consent of its creators, in both the hardware and the accompanying program. The program features an extensive database with a collection of plant species and predetermined characteristics such as the amount of water consumed by the plant, specific placement, ideal soil humidity, temperature, etc. It is also possible to customize and insert a native species of local flora that has not been previously recorded.

Its source code is open and extensively documented, enabling developers to make modifications to both the hardware and software. A digital twin of the robot, with photos of the crop and graphical representations of the plants seeded on the soil is presented in Figure 4.

To gather information about the plants, such as spread area, row spaces, sun requirements, and harvest growth time, the system utilizes openfarm.cc, a website where people around the world can share information about different kinds of plants and crops, considering diverse weather, geology, etc.

The web application operates on a cloud server and communicates with the robot using a standard IoT network protocol, MQTT (Message Queuing Telemetry Transport). Users can create a digital twin version of their vegetable crop raised bed where the robot is installed. With the configuration parameters completed, users can command the physical hardware of the robot. Figure 5 shows a diagram to illustrate the network communication.

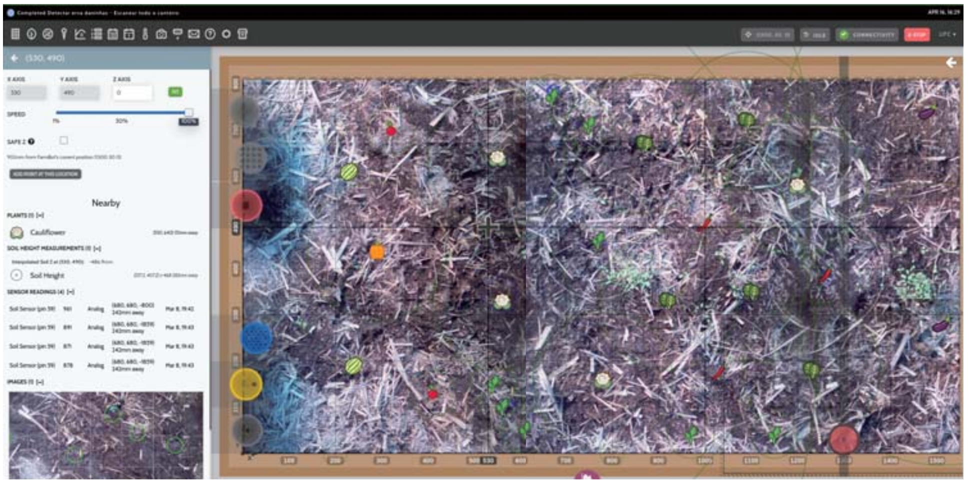


Figure 4. User interface for operation and monitoring.

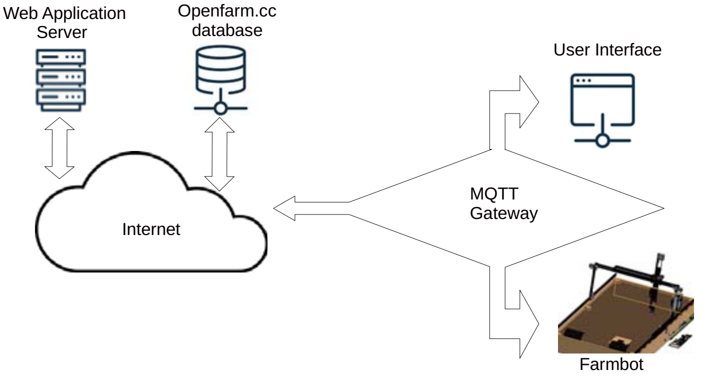


Figure 5. Network Connection Overview.

2.3. Peripherals

2.3.1. Tool mount base

The UTM (Universal Tool Mount) features a coupling and decoupling mechanism based on three strong neodymium magnets installed inside this tool base. The wire connection utilizes four wires (5V Vcc, Ground, tool verification, and analog soil sensor) connected to a pogo pin terminal. Tool verification is achieved by a jump contact between the ground and tool verification contacts. Two pipes are responsible for providing vacuum and water for the seeder and watering tools, respectively. The Figure 6 displays the pin terminals, the ring-shaped magnets and the water and vacuum tubes.

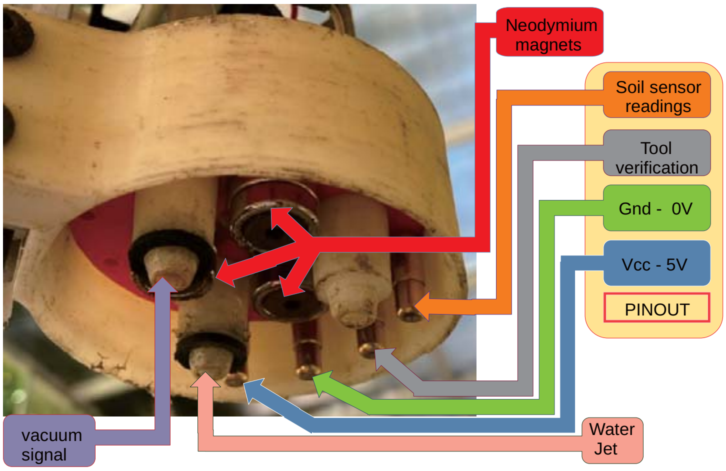


Figure 6. The Botton of the UTM tool

2.3.2. Borescope Camera

The Figure 7 shows the borescope camera used on the robot. This monocular camera is commonly used for pipe inspection applications, but it is also frequently employed as a vision sensor in some machine vision navigation systems for agricultural robots. It provides the benefit of capturing sufficient color and texture information from the environment. Additionally, it is a low-cost, low-power vision device [14]. These characteristics may make it more attractive for low-budget research.

The concept of active perception refers to controlling the data acquisition process in images captured by sensors or cameras. This strategy is designed to minimize potential data loss during the process by adjusting various camera parameters at the time of capturing the image to create the data, such as lens distortion, focal length, and spatial resolution[15].

In the case of the FarmBot-based robot, the original documentation specifies the use of a simple 50-cm fixed-focus borescope camera, witch was replaced by a autofocus boroscope camera.

Figure 7. Borescope camera fixed mouted on the tip of the Z-axis arm.

2.3.3. Soil Moisture Sensor

The variation of soil moisture is measured by an electrical resistance sensor, as shown in Figure 8. The electrical resistance within the pads varies with soil water content. Therefore, the more water that is in the soil means the better the conductivity between the pads will be and will result in a lower resistance. An analog signal is generated proportional to the measured value.

Figure 8. Soil moisture sensor.

2.3.4. Seeder

The seeder tool uses a needle, and as the pump turns on, it creates a vacuum, causing the seed to get jammed in the tip of the needle. Figure 9 shows the seeder mounted on the UTM and the seed bins.

Figure 9. Seeder tool mounted and seeds bin.

2.3.5. Water tool

The water tool functions only as an irrigation diffuser, as shown in Figure 10, this design is important to prevent the water jet from directly hitting the seed or potentially cutting parts of the plants, such as the leaves of vegetables.

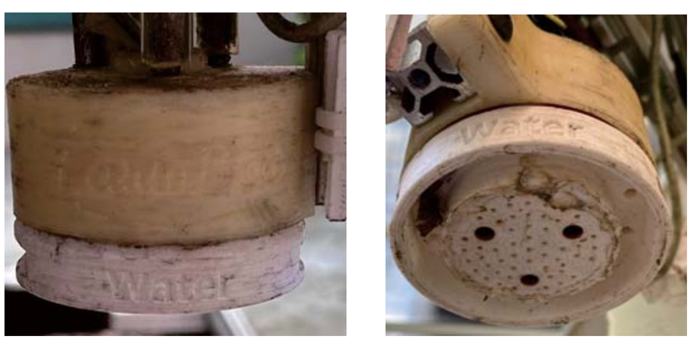


Figure 10. The water tool mounted.

2.3.6. Weeder tool

The Figure 11 displays the Weeder tool, which is equipped with two mounted forks. These 3D-printed forks are designed to eliminate weeds by mechanically smashing them into the soil. This method ensures that the weeds are unable to grow back from beneath the soil surface.

Figure 11. The weeder tool mounted.

3. Automated tasks of the system

3.1. Watering regimens

Different kinds of plants have varying amounts of water consumption, which includes the phases of life of each species. The regimens inserted into the digital twin can manage watering at different times of the day, for varying amounts of water for each plant, and throughout the entire lifespan of each plant in the vegetable crop raised bed, resulting in reduced water consumption. Figure 12 shows the water regiments to water all plants in 9 weeks for 2 seconds at 9:00 a.m. The regiment starts on day one and stops on day 63.

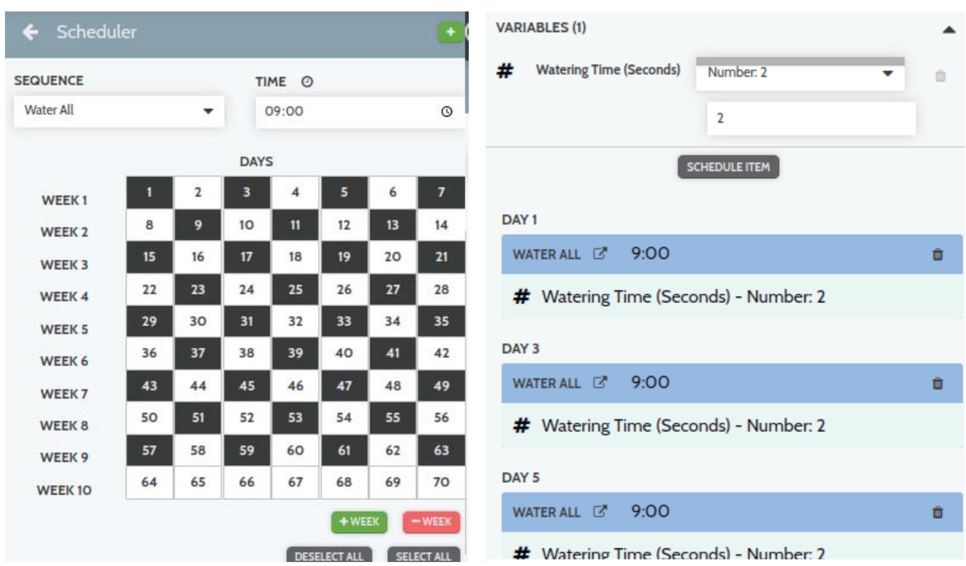


Figure 12. Schedule of the water regimens for all plants.

With the borescope camera the robot can detect if there are weeds growing alongside the planted seeds using a color spectrum border detection algorithm and associate them with the position where the seeds are planted. The color spectrum range can be customized to more precisely detect the leaves of weeds or even the flowers of weeds, such as Serralha (Sonchus oleraceus), found in the South American region, which have variable colors in the range of yellow, pink, purple, and red.

With the use of a moisture sensor, the system can determine if the soil around the plant is dry and then create a logical sequence to skip watering this plant. The Figure 13 shows the soil sensor reading at 1014 on a scale that goes from 1 to 1024. A high value means that the resistence of the soil is higher, and then the soil's more dry. The ideal value of this sensor's reading is in the middle.

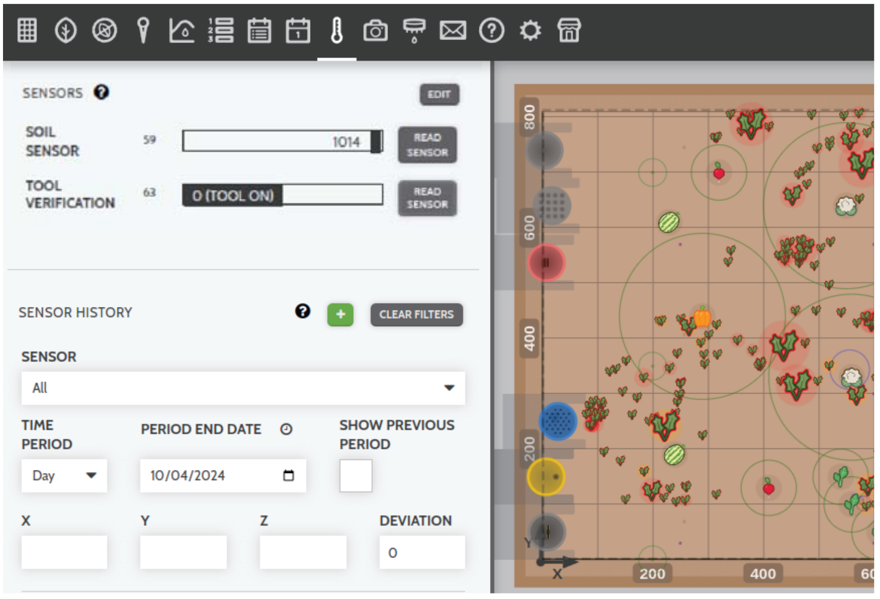


Figure 13. Reading of the soil sensor

3.2. Seeder and seed grains

The seeding mechanism picks up one seed at a time, which it then inserts into the soil. This reduces seed usage for the crop, thereby lowering the cost of inputs. Figure 14 shows, in the leftmost image, the crop option chosen by the user to be planted. Moving to the right, it displays the plants that are already in the vegetable crop raised bed, the seeding tool picking up a seed, and finally, the seeder tool planting a seed in the soil.

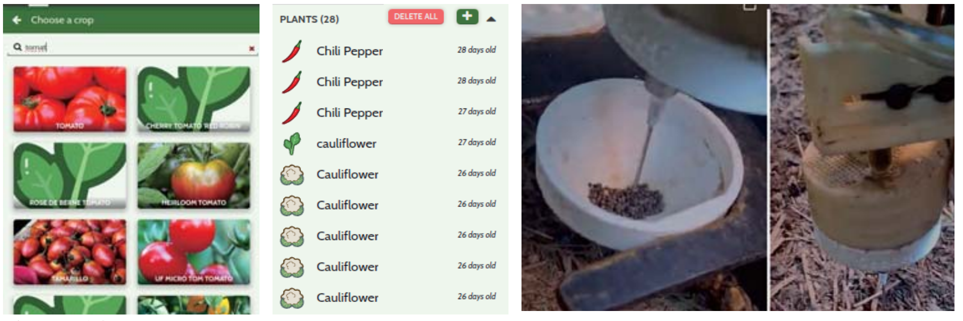


Figure 14. The software to choose a crop to be planted in the raised bed. The seeder tool get the seed and puting on the soil.

3.3. Weed detection through computer vision

The robot Weed Detection System operates based on a computer vision algorithm that uses the color spectrum to identify weeds. Firstly, the weed detection software requires a color range to search for when determining what is a plant and what is soil or another background. In addition, it has sliders for HUE, SATURATION, and VALUE, which are used to select a color range that you want to detect. Finally, the color boxes will give an indication of the selected range, with the green hue usually between 30 and 90 in the color spectrum.

Moreover, once an image is captured by the camera, the software processes this image using the selected parameters. Known (desired) plants are marked with a green circle; detected plants that match the desired plants are marked with a blue circle; and detected plants that do not match the desired plants are marked with a red circle (these are the weeds).

Finally, when WDS detects a plant that does not correspond to the desired plant, it marks it as a weed. The robot can then be programmed to physically remove these weeds using specific tools.

Essentially, the system differentiates desired plants from weeds by analyzing the colors in the captured image and comparing them with pre-calibrated information about which plants were planted by the robot. This allows for accurate detection and efficient removal of weeds.

The Figure 15 shows the weeds grouped and mapped on the vegetable crop raised bed. The weeds are numbered, starting with those closest to the robot's home position, and the trace line shows the trajectory where the robot should go to eliminate them mechanically by pressing them against the soil.

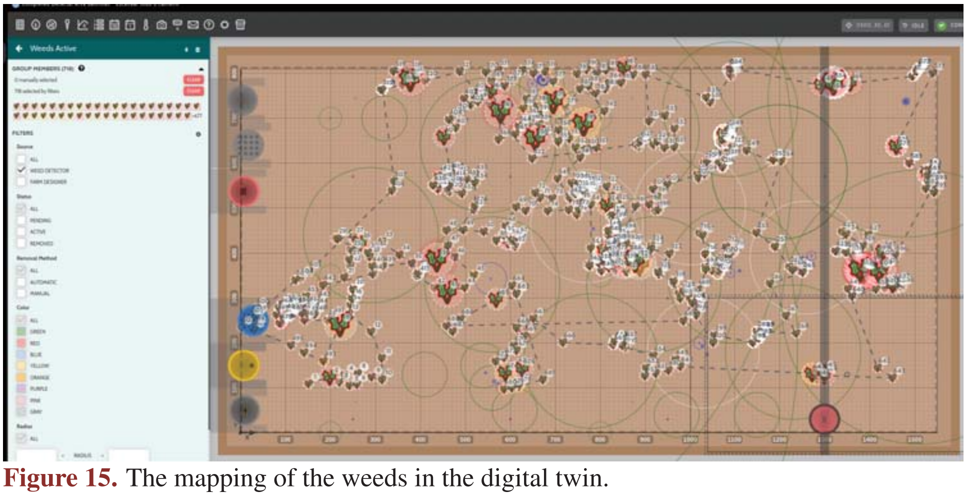


Figure 15. The mapping of the weeds in the digital twin.

Figure 16 shows green circles in the image at the coordinates where the seeds are planted; the red circles are weeds, simulated by leaves in this image.

Figure 16. The weeds are marked with a red circle, while the green points indicate where seeds have been planted.

Fig ure 17 displays a weed screen, where the user can add weeds in groups for future elimination.

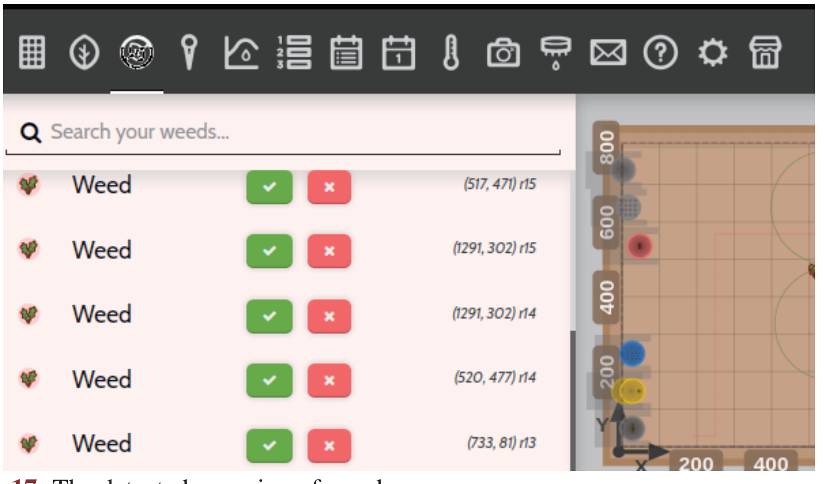


Figure 17. The detected grouping of weeds.

4. Experiments, results and analyses

4.1. The weeds experiment

To evaluate the WDS, different experiments were carried out. Firstly, a test was carried out to detect only weeds that had not previously been entered into the software by the user, in different lighting conditions. After this, tests were carried out varying the color spectrum of the WDS. In addition, tests were carried out by introducing foreign bodies to the system to check the effectiveness of the WDS on foreigners that are in the desired color spectrum, but are not plants.

For all tests, the native WDA was neither modified nor recompiled; instead, the original software, the v15 farmOS compiled image, was installed on the Raspberry Pi.

4.1.1. Weeds experiment through light degradation

To assess the effectiveness of the WDA, 15 plants were planted, 4 of which were actually introduced to the system as plants, while 11 were placed among the seeded plants to simulate growing weeds and to check if the robot accurately counted these leaves. The choice to use green leaves for simulating weeds was made because weeds typically have green parts such as leaves or even the plant stem. The detached leaves were taken from other plants to maintain their green color throughout the test period, thereby simulating the natural green color of the weeds. a series of measurements were taken of weeds detected by the system in the face of light degradation throughout the day, at 10 a.m., noon and 2 p.m. for 8 consecutive days to use the average of the data, since detection can vary. These lighting conditions were influenced by the climate at the test site, which was a sunny day in the northeast of Brazil.

Table 1. Average detections over 8 days.

	10 a.m.	12 a.m.	2 p.m	Real Value
Number of plants detected	7	4	6	4
Number of weeds detected	17	18	16	11
Effectiveness (%)	62.5%	68.2%	68.2%	-

Effectiveness was calculated by dividing the sum of the actual values of plants and weeds by the sum of the detected values of plants and weeds.

As you can see from the Table 1, the algorithm over-detects, which is due to a number of factors:

- **Lighting Conditions:** Variations in lighting throughout the day can cause inconsistencies in detection, as shadows or glare may obscure or highlight certain features of the plants and weeds.
- **Depth of plant:** The baroscopic camera produces a flattened image, resulting in plants of a certain height, depending on the camera's position, appearing to be "prostrate." This distortion causes the plants to fall outside the defined growth radius, leading to their misclassification as weeds. The error can be seen in the Figure 18 highlighted by the arrow.
- **More than one weed detected on the same plant:** A single weed may possess multiple leaves, leading the detector to identify multiple instances of weeds erroneously, as demonstrated in the Figure 18 and 19. This error is also caused by the depth of the plant.
- **Impact of the sun on the edges:** Excessive sunlight can significantly impact weed detection systems by causing over-detection due to the high intensity of luminosity. Such conditions compromise the system's accuracy, leading to false positives and reducing its overall reliability in differentiating between actual weeds and non-target elements in the environment, as evidenced in the Figure 19.

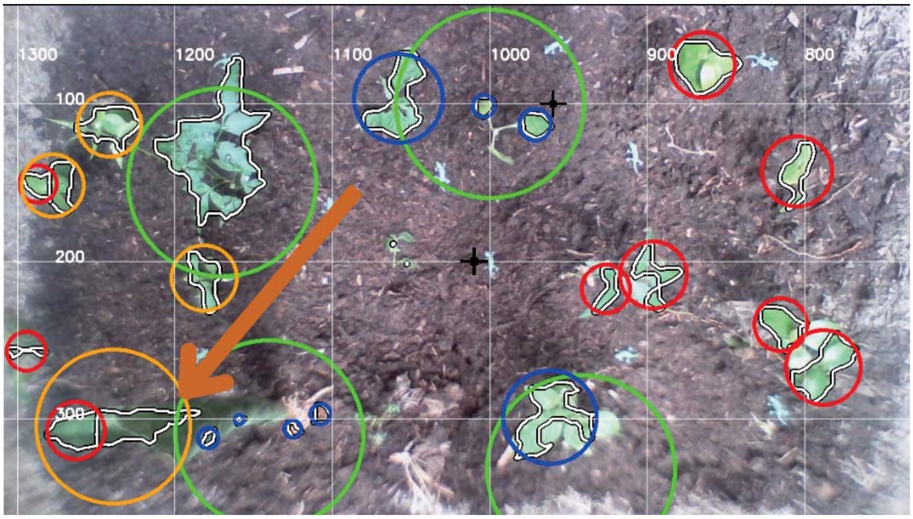
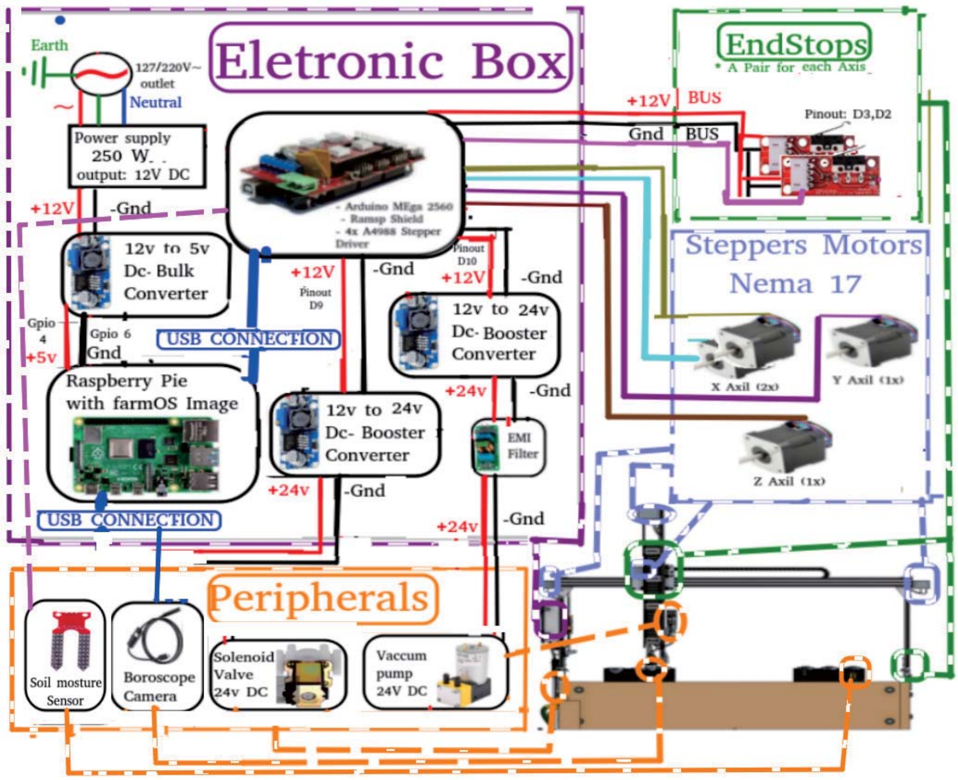


Figure 18. The impact of the depth on the detection.



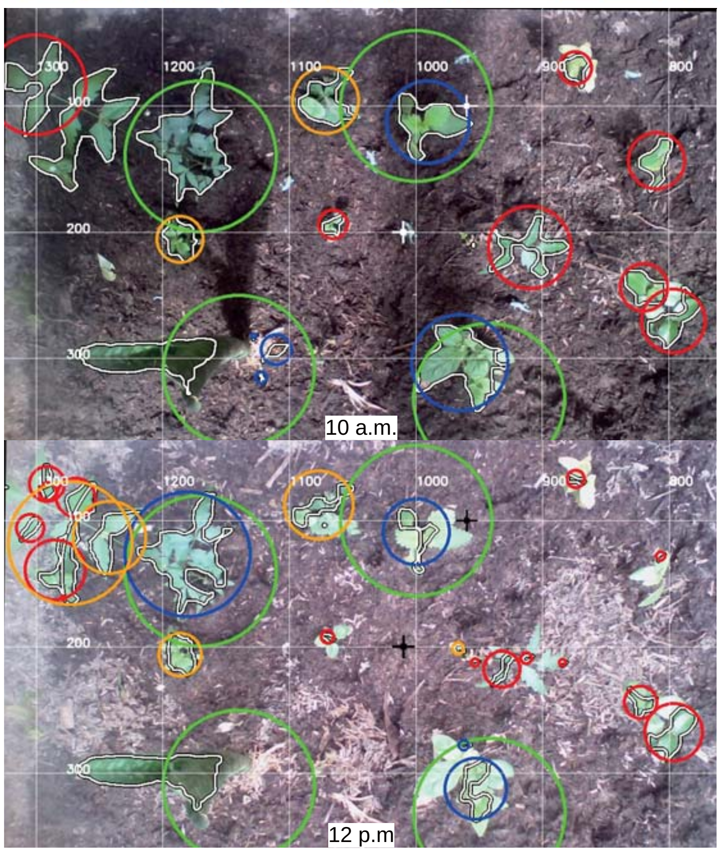


Figure 19. The impact of the sun on the detection.

4.1.2. Change spectrum color to find weed flowers (pink serrilha flowers) experiment

Change the color range causes the WDA takes longer to detect weeds with the altered settings compared to the default green parameters. This measurement cannot be performed by the original software, as it does not provide any response to this task. However, using an external chronometer, the detection time increases by about 2 to 3 times compared to using the green spectrum.The increased time required to detect weeds by changing the color range should not be considered absolute, in fact it is more relative than real time. This is because the WDA mistakenly identifies other objects in the image as weeds.

In this case, the range was deliberately changed to the pink spectrum, resulting in the detection of a large number of nonexistent weeds in the vegetable crop's raised bed, most of which were large soil grains detected as weeds. This error in the identification significantly increases the number of interactions in the native WDA, which in turn increases the server's response time to process all the real and false detection.

This experiment uses a serrilha flower, which has pink petals and is a common weed found in the region of Cear, Brazil. The objective is to determine whether the WDA can identify weeds based on different color spectra, particularly by changing the hue settings from green to pink. All these steps are demonstrated in Figure 20.

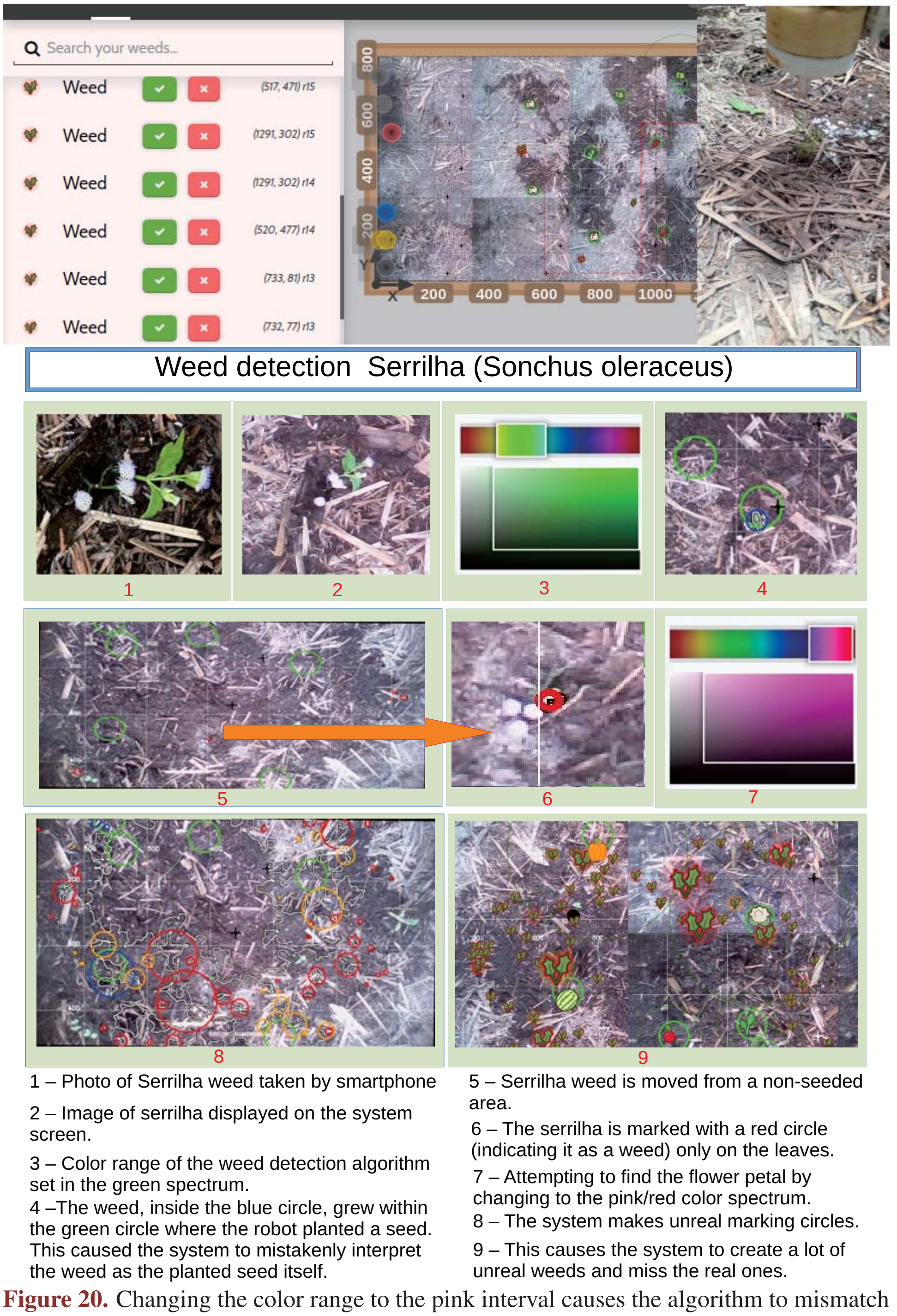


Figure 20. Changing the color range to the pink interval causes the algorithm to mismatch with the real plants.

The variations in the number of object detection's in the three tests can be attributed to color degradation caused by variations in lighting conditions, which affect the coloring of objects throughout the day. This variation leads the WDA to identify some plants, specifically in the case of sow thistle flowers, whose pink hue closely resembles the brown color of the soil. This similarity in color spectra between the flowers and the soil complicates the WDA's ability to identify and differentiate these elements within the crop soil, increasing the challenges faced by the detection system in consistently recognizing and correctly processing image information under variable lighting conditions.

In the three experimental scenarios involving loose leaves, parsley plants, and sow thistle flowers, these were detected as weeds because they were not planted by the system. In cases of manual planting, such as with the parsley plants, the user may have sown the seeds manually without subsequently registering them in the system. To solve this issue, the user can identify the plant and specify the sowing date for the one detected as a weed.

In the case of sow serrilha flowers, the WDA erroneously detected them as weeds, although they were used to simulate mature-stage weeds. This contradicts the logic that weeds do not grow so quickly between two passes of the WCS, suggesting that the WDA struggles to differentiate foreign objects from real weeds.

4.1.3. Foreign body experiment

According to the previous section (4.1.2), it can be inferred that, to improve the system's performance, the color range should ideally be adjusted to the green spectrum. Since most weeds have green leaves and, with the sowing plans coordinated by the user in the system, this should be sufficient to determine whether they are weeds or not. However, there are other green objects that can appear in a plantation, such as loose leaves and insects such as lizards and frogs.

To confirm this inability of the WDA to identify foreign bodies, another experiment was carried out. A total of 40 detections were made in which some lizards and frogs, printed on a 3D printer and painted green, were placed in different positions in the garden bed. This made it possible to analyze how effective the algorithm is at detecting foreign bodies. The flowerbed only had the 4 plants entered by the user into the system and these foreign objects, as you can see in the image. The analysis will take into account the algorithm's ability to detect the plant as a plant and not detect the object as a weed. The following table shows the average of the 40 detections made.

Table 2. Average detections over 40 detections.

	Average	Real Value
Number of plants detected	2	4
Number of foreign bodies detected as weeds detected	7	10
Effectiveness (%)	40%	-

Efficacy was calculated as the average of the effectiveness rates for plants (positive outcome) and weeds (negative outcome), where effectiveness for plants is the ratio of observed to actual values, and for weeds is the reduction ratio relative to the target.

As you can see from the Table 2, the algorithm detects most of foreign bodies as weeds, which confirm the inability of the WDA.

In addition, from the detections it can be seen that the foreign bodies that were not detected as weeds were detected as part of the plant because they were close to the plant's growing radius. As you can see in the Figure 21

Figure 21. Detection of the foreign body as part of the plant.

The Figure 22 shows a experiment by placing some loose leaves and grown weeds, taked from another place, outside the raised crop bed, in the middle of the vegetable crop raised bed. This illustration reveals that the WDA lacks the logic to distinguish between weeds and foreign bodies, such as loose leaves, trash like plastic bottle caps, or even dynamically moving objects like insects.

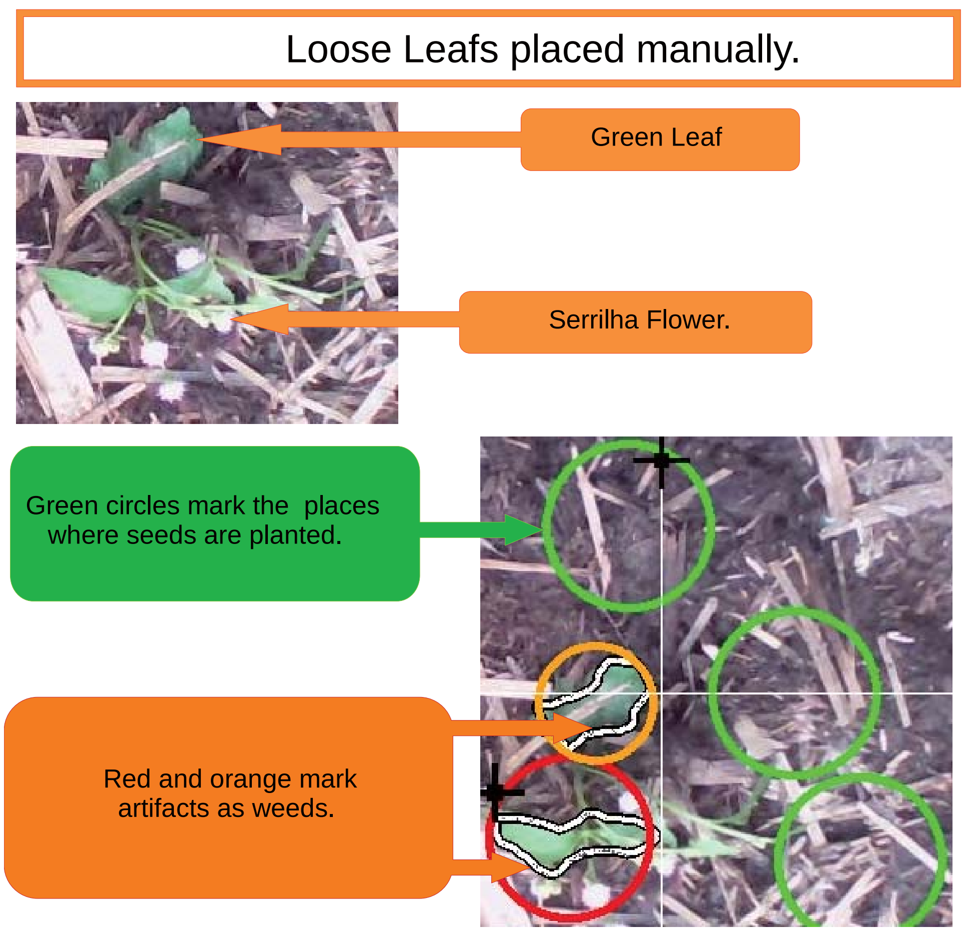


Figure 22. Fake weed detection: the weeds have no history of growing in this area.

4.1.4. Analysis of the experiments

- WDA can't distinguish between weeds and foreign bodies.

  Weeds do not start out large within the crop; instead, they grow gradually each day like any other plant. In the early days of a weed's life, only green parts are visible above the soil surface. This information, along with initial data on the coordinates where these entities are found, can be utilized to develop an algorithm. This algorithm would determine whether an object is a weed or an foreign body, assuming that the foreign body appears unexpectedly at coordinates where previously there was nothing. Insects are less likely to stay in the same region of the crop for an extended period; therefore, they may not be at the same coordinates between the first and second WDS passes. The new WDA strategy should also determine whether the foreign bodies are static or dynamic, helping to decide if the robot should use the weeding tools to eliminate them. If they are previously marked and not found later, this indicates that they are dynamic foreign bodies.

- Light degradation affects weed identification.

  The agricultural sector is fraught with uncertainties in data acquisition and processing. This is due to a variety of factors, including variable environmental conditions, differing sensitivities of sensors, and the inherent unpredictability of agricultural contexts. Such uncertainties can introduce significant inefficiencies into farming operations, affecting everything from planting and harvesting to pest management and resource allocation. The ability to accurately gather and interpret data is crucial for optimizing these processes and ensuring sustainable agricultural practices. [16]
  The color degradation caused due the differences variation in a daylight or even shadows, can be minimized by replacing the monocular camera by stereo cameras or LiDAR sensors, which create 3D geometric models of the scene and objects. This overcomes the issues with shadows and texture changes, enabling better distinction between soil, plants, and foreign bodies[17, 14], however, as mentioned earlier in the section about the borescope camera in this article, it may substantially increase the project's cost.

4.2. Proposed improvements to the WDS

The original fixed focus borescope camera must always be calibrated for this specific focus, above 50cm over the soil, making the Z-axis arm always descends to a fixed point that corresponds to the calibration focus when WDS are used. However, this study introduces an improvement for this robot by employing an auto-focus version of the borescope camera, which allows for rapid adaptation for WDA without the need to lower the arm to bring the plants into focus.

Refine the WDA by adding more processes and changing the strategy; this may help distinguish between weeds and foreign bodies at no additional cost, keeping the original monocular camera .

The flowchart depicted in Figure 23 provides a comprehensive overview of the advanced logic utilized by the new strategy for detecting foreign objects within a crop field. This enhanced strategy increases the basic WDA by integrating additional logical processes to increase accuracy.

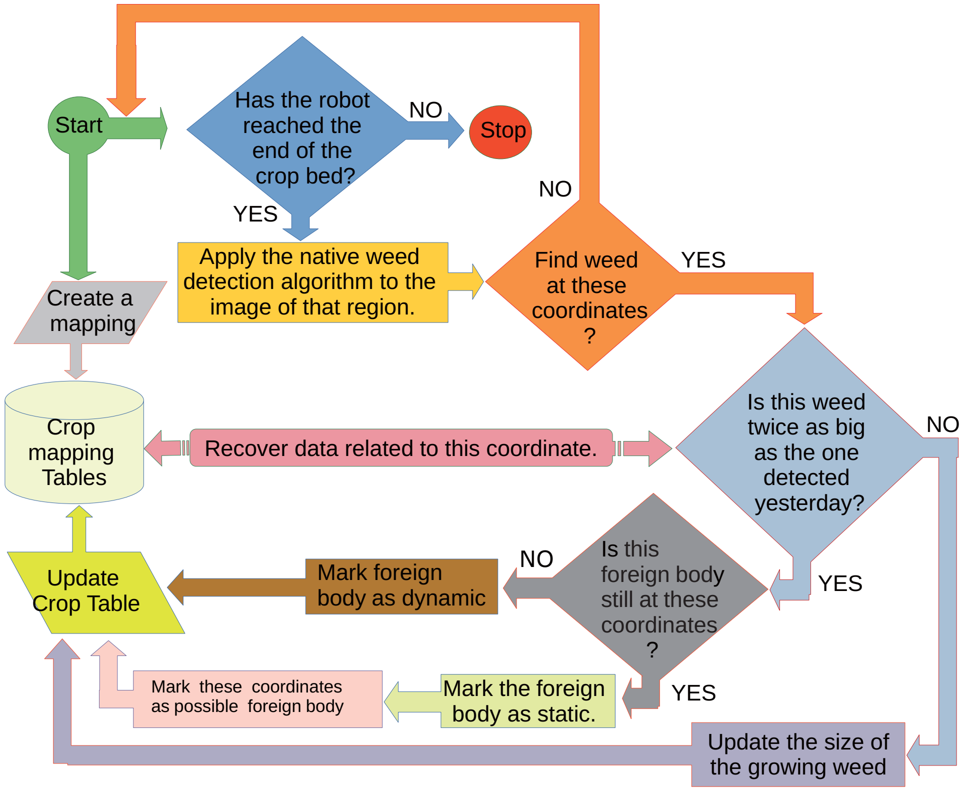


Figure 23. The flowchart illustrates the strategy for detecting foreign bodies by integrating new logical processes into the native WDA.

Initially,the native WDA scans for weeds in images taken from the initial region with the WDS camera, it then progresses to subsequent regions until it covers the entire raised bed. Simultaneously, the algorithm compiles a detailed map of the crop field in the database, incorporating data from the most recent detection session. With each subsequent round of WDS, the database is methodically updated with fresh data, including the dimensions and characteristics of detected objects, noting whether they are static or dynamic relative to the surrounding crops.

The principal method to determine if an object is an foreign body involves comparing the object's radius size at those coordinates against the historical data stored in the database. If the radius size of a newly captured image at that coordinate is at least twice as large as the one previously recorded, the object is identified as an foreign body. This decision criterion is founded on the understanding that a plant cannot undergo such rapid growth from its seedling or early growth phase to a mature stage between two consecutive WDS rounds. Such a significant increase in size within this brief period strongly suggests the presence of an foreign body above the soil.

Upon identifying an foreign body, the secondary logic process commences, which involves distinguishing whether the object is static or dynamic. This determination is made by evaluating if the foreign body consistently appears in the same location in consecutive images. If it does and is recorded as such in the database, the foreign body is classified as static. Conversely, if its location varies between images, it is considered dynamic.

4.2.1. Applying new logical processes to images for detection

To evaluate the effectiveness of the proposed algorithm, the same set of images previously processed with the native WDS algorithm were reanalyzed using the newly developed approach. The results are presented in Table 3.

For a fair comparison, the number of plants detected was kept consistent, as the new algorithm does not alter the plant detection process.

Table 3. Average detections over 40 new detections.

	Average	Real Value
Number of plants detected	2	4
Number of foreign bodies detected as weeds detected	0.5	10
Effectiveness (%)	72.5%	-

Efficacy was calculated as the average of the effectiveness rates for plants (positive outcome) and weeds (negative outcome), where effectiveness for plants is the ratio of observed to actual values, and for weeds is the reduction ratio relative to the target.

Figure 24 illustrates the application of the new algorithm to the images, where red circles denote weeds and white circles indicate foreign bodies. As shown, with each detection iteration, the number of foreign bodies identified decreases, demonstrating the algorithm's improved precision and effectiveness in distinguishing relevant elements. This reduction underscores the algorithm's potential for enhancing detection accuracy in practical applications.

As evident in the table, the efficiency has significantly improved, highlighting the effectiveness of the proposed algorithm when integrated into the WDS framework. This demonstrates the algorithm's potential as a valuable enhancement to the system. Further optimization and refinement of the algorithm are recommended to maximize its performance before full implementation within the native WDS.

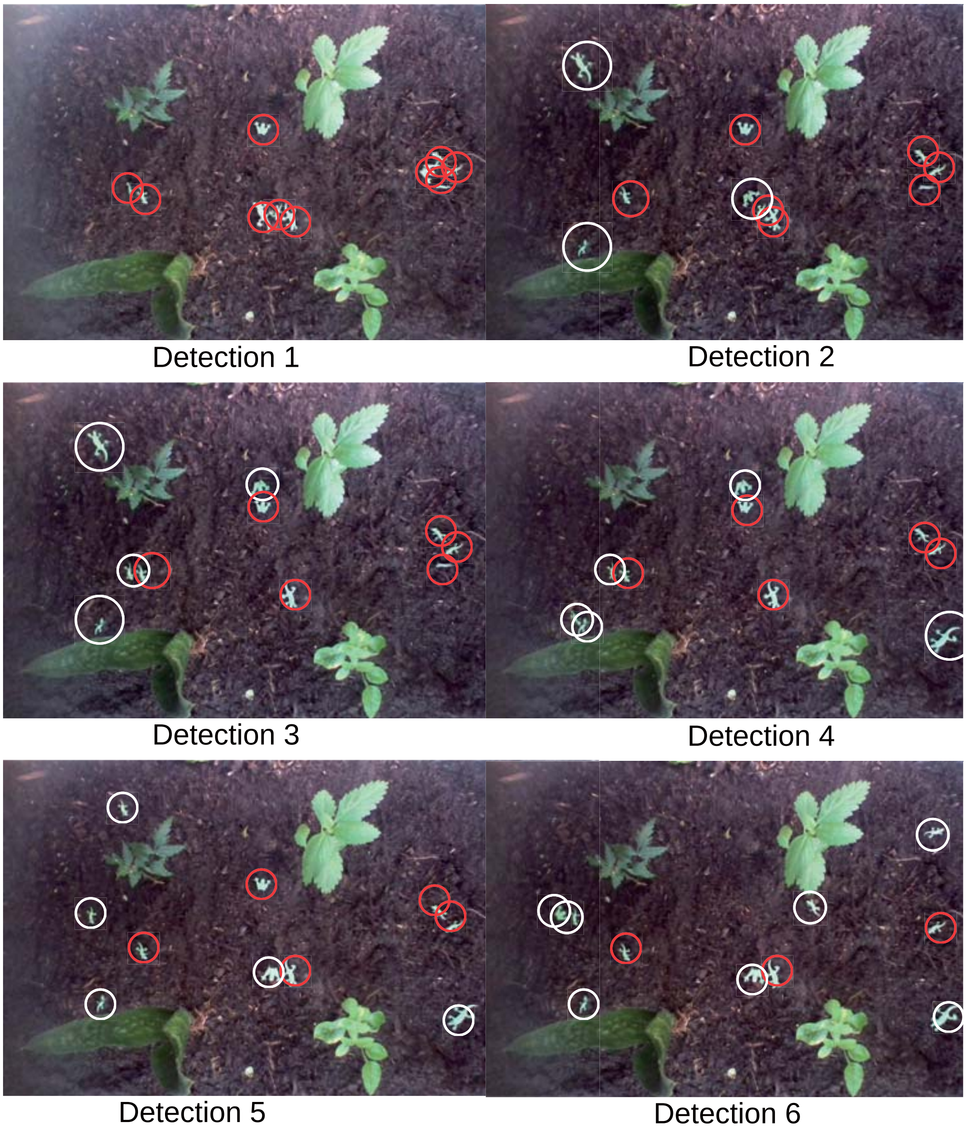


Figure 24. Application of the new algorithm on image analysis.

5. Conclusions

The robot demonstrates substantial potential to serve as both an innovative development platform and a practical crop management tool. It offers a vast array of opportunities for researchers to delve deeper into its capabilities. Acting as a base for numerous projects, it enables advancements in its own functionality as well as in broader agricultural technologies.

The platform's user-friendly interface makes it attractive and accessible, simplifying adoption and utilization for a wide range of users. This precision agriculture tool allows crop owners to significantly reduce their budgets for inputs such as fresh water, seeds, and weed killers.

Replacing the borescope camera with an autofocus model, instead of the original fixed-focus one, demonstrates that the algorithm helps to enhance the speed of weed detection process.

Further exploration and refinement by researchers could significantly enhance the robot, for example, by improving the WDA. Although using a stereo camera instead of a monocular one, with a complex algorithm and more robust hardware, should resolve the foreign body problem, this also involves an increased cost of the project and research in the matter, along with a major restructuring of the software, especially in the native WDA. Adopting a new strategy to identify foreign bodies, such as loose leaves among the crops and not just the weeds, could greatly enhance its efficiency and usability in real-world scenarios and minimize the limitations of the native WDA. However, this does not replace the algorithm; in fact, it uses it as the centerpiece of this new strategy, while maintaining the low-cost use of the monocular camera.

Solving these and other technical challenges will enable the robot to become even more precise in the future, thereby increasing its efficiency and optimizing agricultural practices and outcomes.

This robot represents a promising system for research and development in robotic applications for agriculture. Continued advancements in this area could lead to groundbreaking changes in how technology is used to enhance crop management and agricultural productivity. This underscores the critical role that innovative robotic solutions play in the future of agriculture. Hopefully, future studies will use this robot platform as a base for improvements or enhancements of the robot itself.

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