

Towards Cost-Effective Robotic Solution for Agricultural Data Acquisition

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Abstract—As the demand for data in precision agriculture increases to enhance productivity and sustainability, the acquisition of this data becomes critical. Currently, data acquisition processes often rely on manual methods or stationary platforms, which limit scalability and flexibility. Although autonomous vehicles present innovative solutions, they face challenges such as high costs and limited adoption rates, especially among small-scale farms. This paper introduces a cost-effective, mobile robotic platform for autonomous data collection in agricultural environments. Moreover, our platform provides scalability, accuracy, and affordability, democratizing access to precision agriculture technologies. The platform utilizes a standard camera mounted on its arm, guided by ArUco markers—digital markers designed for high precision—strategically placed within the monitoring environment. These markers give the robot high-level commands necessary for an effective data acquisition campaign. Our preliminary results show that leveraging open-source robotic projects and off-the-shelf components allows the proposed autonomous robotic system to adapt to various crops and terrains effectively in both simulated and real scenarios. Thus, it offers a viable alternative to more costly data acquisition solutions.

Index Terms—agricultural robots, precision agriculture, data collection, data acquisition, agricultural datasets.

I. INTRODUCTION

Agriculture is highlighted as a pivotal sector for ensuring global food security and driving economic growth, as emphasized by the United Nations (UN) in their 2030 Agenda for Sustainable Development [1]. Therefore, this sector is undergoing a rapid, incremental transformation to meet the anticipated growth demands. In this context, Precision Agriculture (PA) enhances resilience, sustainability, and efficiency by optimizing resources based on high-quality, high-granularity data collection and advanced data processing techniques driven by Artificial Intelligence (AI) [2]. Recent surveys have showcased Machine Learning (ML) / Deep Learning (DL) applications such as the detection of fungal attacks in crops, detection of plant diseases and pests in tomatoes, and crop yield estimation [3]–[5]. Furthermore, these surveys highlight that computer vision is favored in agriculture over other sensing techniques due to its versatility, efficiency, and cost-effectiveness, while enabling non-destructive, non-contact data collection. Nonetheless, the effectiveness of these applications relies on the quality and quantity of the agricultural datasets, which include a wide array of information such as crop yields, soil characteristics, and pest occurrences, among others [6].

However, most currently available datasets are created using handheld methods or ground-fixed platforms [6]. These setups

demand consistent monitoring amid constraints such as power supply and connectivity issues, which hinder scalability [7]. Moreover, stationary platforms may overlook vital changes in soil conditions, crop health, or weather fluctuations, thus limiting their flexibility [8]. An innovative solution involves employing autonomous vehicles, such as unmanned aerial vehicles (UAVs) or unmanned ground vehicles (UGVs), equipped with advanced imaging sensors [9]. Yet, current research for UGVs has primarily focused on indoor environments [10], while UAVs introduce additional limitations, including high costs, limited flight endurance, and payload capacity constraints [11].

Furthermore, adoption rates of these autonomous data collection methods are notably higher among large-scale operations, leaving many small farms behind [2]. Limited access to financial resources, technical expertise, and infrastructure often hinders the ability of small-scale farmers to implement these innovations effectively [12]. This discrepancy underscores the importance of addressing the digital divide in agriculture to ensure that all farmers, regardless of size, can access the benefits of precision agriculture [2]. Small farms play a crucial role in global agriculture, collectively contributing to a significant portion of the world’s food supply [13]. Therefore, efforts to democratize access to modern agricultural technologies must prioritize including and empowering small farms with access to robust agricultural datasets and effective, accurate, and scalable data collection methods.

This paper presents a cost-effective, modular robotic solution specifically designed for agricultural data acquisition. We introduce an autonomous robotic platform that streamlines labor-intensive data-gathering tasks in the agricultural sector, offering scalability, accuracy, and affordability. Our approach aims to democratize access to precision agriculture technologies, empowering farming businesses to leverage advanced data collection and analysis capabilities for informed decision-making and operational optimization. To validate our solution’s efficacy, we implemented a proof-of-concept (PoC) emphasizing cost-effectiveness. We then rigorously evaluated the platform’s autonomy, scalability, and precision in both simulated and real-world scenarios. Our findings demonstrate that our proposal offers a cost-effective way to enhance data collection efficiency, particularly benefiting small-scale operations in generating precise datasets crucial for advancing data processing in precision agriculture.

The remainder of the paper is organized as follows: Sec. II

outlines the key system requirements and provides an overview of the proposed solution. Sec. III describe a use case and a proof-of-concept implementation of our proposal. Sec. IV details three experiments along with their results and analysis. Lastly, Sec. V offers conclusions and looks forward to future research directions.

II. PROPOSED ROBOTIC SOLUTION

We propose an autonomous robotic platform to streamline labor-intensive data-gathering tasks to create high-quality and accurate agricultural datasets. Furthermore, we focus on the requirements of small farm operations to make precision agriculture technologies accessible to a wider audience [2], [13], [14]. Therefore, we can summarize the requirements of our platform as follows:

- R1 **Quality and Accuracy:** the primary objective of the platform is to generate precise and reliable datasets. Therefore, it is imperative that the platform offers an accurate streaming method for this process.
- R2 **Autonomy and Adaptability:** the agricultural environment is diverse and variable. Therefore, robotic solutions must be versatile and easily adaptable to different crops, field conditions, and tasks. This adaptability should be achievable with minimal physical intervention, allowing for quick and easy reconfiguration of the robots for various agricultural operations.
- R3 **Affordability:** the robotic system cost may be the most critical factor. The initial investment and ongoing operational expenses must align with the financial realities of these businesses, which often operate with slim profit margins. Industrial solutions are almost always focused on large agricultural businesses dealing with extensive fields, making their price often prohibitive for smaller companies.
- R4 **User-Friendly Operation:** the complexity of operating these technologies is another significant barrier. Agricultural robots should be designed with user-friendliness, requiring minimal training for operators. This requirement is crucial in an industry where workers may not have advanced technical skills or experience with sophisticated machinery.

The proposed robotic solution, as illustrated in Fig. 1, is designed taking into consideration the requirements previously described, both from the data collections perspective (*R1* and *R2*) and from the small farms perspective (*R3*, *R4*). The following paragraphs describe our proposal, divided into hardware and software designs.

A. Hardware design

At the hardware level, our proposal includes three main subsystems, namely a vehicle base, an arm-mounted camera (comprising a manipulator and a visual camera), and a navigation system.

- **Vehicle base:** the foundation of our robotic solution is a sturdy vehicle (identified as *A* in Fig. 1), engineered to navigate challenging terrains. This capability allows

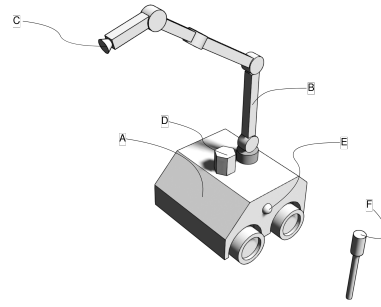


Fig. 1. Conceptual model of the proposed solution.

the robot to operate in diverse agricultural landscapes, ranging from smooth, expansive fields to irregular, rough terrains. This adaptability is key for a design that is broadly applicable in various farming settings without significant modifications to the original design, addressing requirements *R1* and *R2*.

- **Arm-mounted camera:** another key subsystem of the proposed robotic platform is its arm-mounted camera, which is essentially a manipulator equipped with a visual camera as its end effector (identified as *B* and *C* in Fig. 1). This design accommodates two crucial adaptability functions. In particular:
 - 1) **Enhanced Data Collection:** Unlike fixed cameras firmly affixed to the structure of the rover, the arm can maneuver to capture images from varied angles and perspectives, accommodating different types of crops and field conditions. Therefore, this subsystem offers increased dexterity to the platform, allowing for superior data collection capabilities in terms of quality and quantity, addressing requirements *R1* and *R2*.
 - 2) **Versatile Imaging Solutions:** The manipulator's end effector is ingeniously designed to support various camera types, from high-resolution digital cameras for detailed imagery to thermal cameras for monitoring crop health and multispectral cameras for assessing plant growth. This modular approach to camera integration allows for tailored data collection, perfectly aligning with the unique requirements of each agricultural application. Such adaptability guarantees that the robot can capture diverse visual data, making it an invaluable tool for precision farming and advanced agricultural analysis, addressing requirements *R1* and *R3*.
- **Navigation System:** to ensure proficient navigation in outdoor settings, our design incorporates a LiDAR sensor (identified as *D* in Fig. 1), which utilizes time-of-flight technology. This approach makes it less prone to interference from lighting conditions than structured-light sensors, rendering it more apt for the fluctuating outdoor conditions encountered in agricultural settings. This selection guarantees dependable navigation across diverse lighting and weather scenarios, addressing requirement

R2.

B. Software design

At the software level, we identify two main subsystems : Point-of-Interest (POI) selection and enhanced agricultural intelligence modules. More in detail:

- POI Selection:** A fundamental feature of our robotic system is its user-friendly interface, designed to simplify how agricultural workers designate points of interest for monitoring. To enhance accessibility and reduce the necessity for extensive training, our approach integrates a specialized sensor (marked as *E* in Fig. 1) that recognizes environmental markers (marked as *F* in Fig. 1) to identify these critical points. This method ensures an intuitive and rapid configuration of the robot’s data collection and monitoring tasks, eliminating the need for end-users to master complex software tools, addressing requirement *R4*.
- Enhanced Agricultural Intelligence:** This module leverages state-of-the-art ML/DL tools, enabling modern mission planning and navigation across designated regions of interest (ROIs) where the POIs are pinpointed. It also incorporates advanced computer vision algorithms to efficiently and effectively analyze images captured by the end-effector camera, extracting crucial data. This integrated approach ensures that the robotic system can precisely navigate the complexities of agriculture, addressing requirement *R2*.

III. PROOF OF CONCEPT AND USE CASE

To properly evaluate the proposed modular platform’s ability to meet the primary system requirements *R1 – R4*, we defined a specific use case for the robot and then set up a tailored configuration of components and modules as outlined in Sec. II. Specifically, the robot’s task is to autonomously collect pictures of the same outdoor agricultural scenes with the goal of compiling valuable image datasets for training Machine Learning/Deep Learning (ML/DL) algorithms [6]. The crucial property of these datasets is their granularity and high quality, which are critical for successful algorithm training, as stated by requirement *R1*. It is important to note that “high quality” here does not pertain to the images’ resolution or pixel count. Rather, it signifies the consistent and accurate depiction of the scenes over time. Such precision is vital because the value of the datasets primarily depends on their accurate representation of the scenes, a crucial component for efficiently training ML/DL models. Concerning the kind of visual images to collect, there are no specific limitations, therefore, depending on the cost of the image collection equipment, the total cost of the platform can range from a few thousand to tens of thousands of Euros. This flexibility in cost ensures that the platform is accessible to a broad spectrum of agricultural operations, particularly for small-sized farms, satisfying *R3*.

The data acquisition process is graphically represented in Fig. 2. Briefly, the robot begins its task by navigating a pre-programmed route instantiated through the mission planning

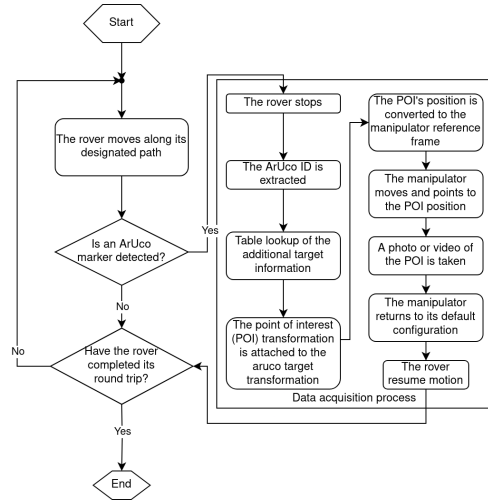


Fig. 2. Flowchart of the data acquisition process.

and navigation software components. For autonomous navigation purposes, a LiDAR sensor guides the robot, ensuring it covers all the ROIs identified by farm workers. While traversing its designated path, the robot constantly looks for physical markers placed throughout the field. These markers indicate POIs where data needs to be collected. Therefore, upon identifying a marker, the robot stops and adjusts its manipulator arm based on the additional information associated with the detected POI. Since the arm is equipped with a visual sensor at the end, upon a correct recognition of the POI, the visual camera is correctly oriented to collect the necessary visual data efficiently. Once data collection at a specific marker is concluded, the robot resets its manipulator and camera to their original positions and proceeds along the set path. It continues to scout for new markers to initiate subsequent data captures or completes its route if no further markers are found. This automated approach permits the robot to gather comprehensive, specific data throughout the expansive agricultural area, requiring minimal human oversight.

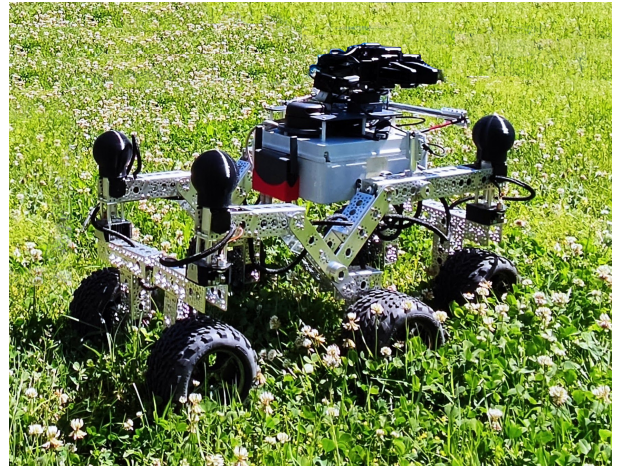


Fig. 3. A picture of the assembled robot.

To implement the outlined use case, at the hardware level, we selected the do-it-yourself (DIY) version of the Jet Propulsion Laboratory (JPL) rover¹. This vehicle stands out due to its distinctive features, rendering it an ideal mobile base for our agricultural inspector robot. The inclusion of a rocker-bogie suspension system is a key benefit, ensuring continuous contact of all wheels with the ground, which is crucial for navigating diverse terrains. The differential pivot mechanism plays a significant role in evenly distributing ground forces across the wheels, thus facilitating smoother navigation across varied landscapes. Moreover, the 6-Wheel Ackerman Steering system contributes to the vehicle’s stability and ensures effective traction, even during tight turns or on complex, uneven paths. This selection effectively meets the requirements *R3* and *R4* by being significantly cost-effective compared to other options with similar capabilities and by being open-source, which offers extensive documentation for everyday use and potential adaptations.

For the arm component, we chose the OpenManipulator-X, a compact 4-degree-of-freedom (DOF) manipulator by Robotis². Despite its compactness and lightness, it offers a satisfactory payload capacity, meeting all our requirements: it is more affordable than many alternatives, features a simple and user-friendly design for easy maintenance, and comes with hardware specifications and control software that are openly available under open source licenses, ensuring ease of use and extensive customization options. To accommodate a visual camera at its end-effector, we modified the manipulator by replacing its original grasping tools with a custom-designed 3D printed mount tailored for the specific camera sensor we are using (see Fig. 3).

For navigation purposes, we chose the RPLIDAR A3 by SLAMTEC³, a 2-dimensional LiDAR sensor that has been recently released on the market. This sensor is notably more affordable compared to other commercial alternatives, thereby satisfying requirement *R3* effectively. Despite its exclusively commercial availability not meeting all our specified requirements, its full compatibility with the Robotic Operating System (ROS) significantly eased its integration into our project, allowing for straightforward setup.

For the identification of POIs within the data collection system, we opted for standard ArUco markers, that are 2-dimensional bar codes widely utilized in computer vision applications. Employing these markers enables the detection of a POI’s presence and accurately determines its position and orientation in three-dimensional space relative to the robot. Additionally, printed markers represent a user-friendly, affordable and non-invasive solution for identifying POIs. To facilitate the detection of these markers, we equipped the robot with a secondary, low-resolution, fixed camera mounted on its side.

Additionally, on the software side, as previously mentioned, we chose the Robot Operating System (ROS) for our platform⁴. ROS is a middleware that offers software libraries and tools specifically designed for robotics applications. It was installed on a Raspberry Pi 4⁵ and facilitates the interaction and coordination between all the hardware and software components of our robotic platform. Thanks to its modular architecture and the availability of its components under free and open source licenses, it meets all our platform’s requirements. Moreover, we utilized the ROS Navigation Stack, which leverages data from the LiDAR sensor mentioned earlier, to provide basic navigation capabilities for our robot, enabling it to autonomously navigate within its environment. Additionally, the software implementing the data collection loop has been developed from scratch, rather than relying on pre-existing software provided by ROS or any other open-source library.

Lastly, for simulation purposes, we selected Gazebo⁶, an open source robotic simulation framework mainly used during the preliminary testing phases to evaluate the viability of our solution. The simulated environments comprised a mix of fruit trees (to simulate apple or pear orchards) and small shrubs (to simulate mixed berries) and varied in the type of terrain, ground trajectory, and POI definitions.

IV. PRELIMINARY RESULTS

To assess the effectiveness of the proposed robotic platform, we conducted three initial experiments designed to measure the performance and identify any potential constraints of the system’s components. In particular, these experiments focus on the Quality and Accuracy of the data collection (*R1*) and the Autonomy and Adaptability of the platform (*R2*).

A. First experiment: OpenManipulator-X control accuracy

In order to assess the quality of the control of the manipulator, we thoroughly tested the end-effector position accuracy of the out-of-the-box control software. In this experiment the manipulator’s workspace has been uniformly discretized as the surface of spheres of radius *30cm* and *37cm* centered on its base. Each discretization, limited on the surface of the spheres achievable for the manipulator, produced 24 spatial coordinates and each coordinate has been tested starting from 3 different initial configurations. The total number of samples produced was 432. The position error has been defined as:

$$e_{ee} = P_d - f(q), \quad (1)$$

in which e_{ee} is the end-effector error vector, P_d is the desired end-effector position obtained from the workspace discretization, and $f(q)$ is the forward kinematic function applied on the configuration q read from the motor’s encoders. Fig. 4 presents the results of the experiment, categorized by spatial axis and sphere radius. The test reveals that, despite the absence of gravity compensation (evident from the disparity

¹<https://jplopensourcerover.com/>

²https://manual.robotis.com/docs/en/platform/openmanipulator_x/overview/

³<https://www.slamtec.ai/product/slamtec-rplidar-a3/>

⁴<https://www.ros.org/>

⁵<https://www.raspberrypi.org/>

⁶<https://classic.gazebosim.org/>

in error along the Z axis compared to others), the observed error remains within acceptable limits for our application, successfully validating requirement *R1*.

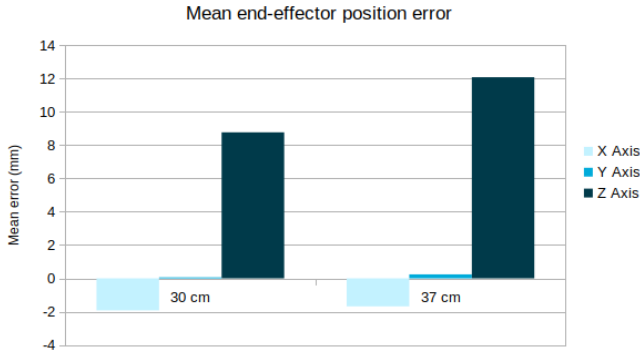


Fig. 4. Observed end-effector’s position error.

B. Second experiment: quality of ArUco detection

This experiment aims to understand how well the marker detection system performs under different conditions and settings, providing valuable insights into its reliability and operational limits. To execute it, a Raspberry Pi computer equipped with ROS and a low-definition camera (640 × 480 @24 fps) was mounted on a custom-built table, while an ArUco marker was attached to a wooden support placed on a mobile base. The camera observes the environment and feeds the video to the detection software, which scans each frame for the presence of the ArUco marker, providing data on whether the marker is detected in each frame and its location. A measuring tape is used to measure the distance between the camera’s support and the mobile base as the marker is gradually moved away. This process is continued until the marker is too far to be detected by the system. The experiment was conducted under two different lighting conditions to assess the system’s performance variability:

- Indoor (with artificial lighting): the initial test was done indoors using the room’s lighting.
- Outdoor (with natural lighting): to compare, the test was also conducted outdoors, relying on sunlight for illumination.
- Indoor (tuned): a second indoor test was conducted with the software parameters adjusted (“tuned”) to optimize the system’s detection capability under artificial lighting conditions.

The results of the experiments were categorized into two levels, based on how well the system detected the marker:

- Optimal detection: represents the best-case scenario where the system detects the marker in every frame without fail. This represents the system’s ideal performance under stable conditions, indicating it operates perfectly under the given conditions.
- Unstable detection: this category acknowledges that, while the system does not achieve perfection, it still

detects the marker most of the time. Occasional failures to detect the marker in some frames are considered acceptable for the purposes of this experiment.

As illustrated in Fig. 5, the ArUco markers could be precisely detected and located from several meters away, even under suboptimal lighting conditions using a low-resolution camera. However, the experiments consistently highlighted a critical limitation: the partial occlusion of the ArUco marker significantly impaired the software’s detection capabilities. While such issues can be readily addressed in a controlled setting, it is crucial to acknowledge the challenges they may pose in practical agricultural applications. This underscores the need for additional strategies and considerations to mitigate occlusion effects in real-world scenarios.

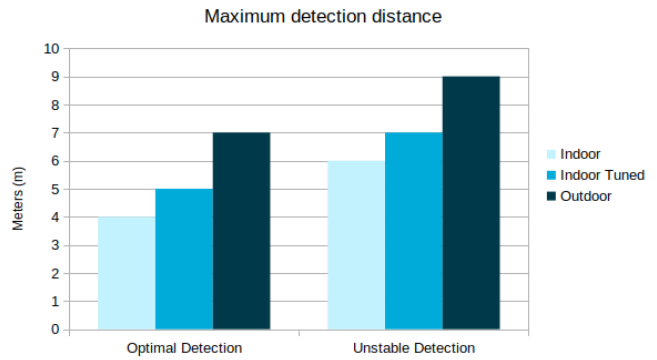


Fig. 5. Peak detection ranges achieved in the experiment.

C. Third experiment: Round-trip assessment

Simulated outdoor environment: we first conducted a series of tests using a simulated version of our agricultural robot in the Gazebo framework. These tests were carried out in two distinct virtual environments, each designed to replicate different agricultural scenarios. The environments included a variety of elements such as fruit trees, mimicking apple or pear orchards, and small shrubs, representative of mixed berry fields, as shown in Fig. 6. Factors such as terrain type, ground trajectory, and POI definitions were varied to comprehensively evaluate the robot’s performance. During these virtual tests, we observed several limitations of the system:

- Image tilt: primarily due to the manipulator’s limited degrees of freedom, which restricted its ability to adjust for varying ground steepness. Depending on the software in which the images are processed, it could be inconsequential.
 - Inadequate detection of low-level obstacles: the onboard 2D LiDAR sensor showed limitations in detecting small ground-level obstacles, such as boulders and holes, which is crucial for navigating through complex agricultural terrains.
 - Unachievable POIs: some POIs were found to be unattainable due to their specific orientation requirements.
- Despite these challenges, the virtual tests also revealed promising aspects of the system. Notably, there was a significant

degree of synergy observed between the robot's components. The integration of the arm-mounted camera and the POI defined by ArUco markers in the environment functioned effectively in most scenarios, underscoring the potential of the system in real-world agricultural settings.



Fig. 6. Simulated agricultural scenarios using Gazebo (POIs are defined using ArUco markers).

Real outdoor environment: encouraged by the results of the simulated tests, we conducted outdoor tests to effectively evaluate the navigation capabilities of our robotic prototype. The prototype was tested in a real-world outdoor setting, designed to mimic the conditions it would encounter in typical agricultural scenarios. The testing environment included various terrain types to thoroughly assess the robot's navigation system. The robot demonstrated a strong ability to navigate across different types of terrain and consistent and reliable performance in outdoor settings, showcasing its adaptability to diverse environmental conditions commonly found in agricultural settings, successfully validating requirement *R2*.

V. CONCLUSION AND FUTURE WORKS

Precision agriculture's effectiveness hinges on collecting vast, high-quality data from fields, a task hampered by the limited accessibility to cost-effective, autonomous data acquisition technologies.

This paper presented the design and development of a cost-effective, autonomous ground robot with an arm-mounted camera. The robot is designed to navigate and collect data in various agricultural settings, guided by the presence of physical markers codifying high-level commands for the robot. To validate the goodness of our proposal, we implemented a fully functional proof-of-concept, and evaluate in a real world use case.

Our tests demonstrated the robot's capability in marker detection, manipulator control, navigation, and virtual simulations, highlighting its potential as an agricultural data

collection tool. Furthermore, the affordability of our platform, combined with its preliminary success in navigating diverse terrains and detecting markers, indicates it is a valuable asset for agricultural research and practices. Thus, despite current challenges (e.g., component quality and the manipulator's limited movement), our robot marks a promising advancement in agricultural robotics, with future enhancements essential for its widespread adoption.

Future works include additional real-world experiments to validate the autonomous navigation further, evaluate different sensors (e.g., hyperspectral cameras), and test other visual markers for the arm's instructions.

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