Overcoming Limitations of IoT Installations: Active Sensing UGV for Agricultural Digital Twins

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***Abstract*—The Digital Twin (DT) concept has gained attention for its potential to enhance agricultural productivity and sustainability by creating virtual replicas of physical objects or environments. Fixed IoT installations enable the implementation of DTs as one of the main data sources; however, they introduce reliability, scalability, and cost limitations. Furthermore, these installations may miss crucial environmental changes, impacting the value of the collected data. This paper proposes an Unmanned Ground Vehicle (UGV) as an active sensing platform for enabling agricultural DTs. It integrates a mobile base with a modular sensing payload, including imaging and environmental sensors, to autonomously gather field information. The platform can replicate fixed IoT installations by incorporating a robotic arm, creating time-series datasets for comprehensive farm monitoring. Additionally, the platform can adapt to environmental changes by leveraging Edge AI and distributed learning techniques in the data collection process. To validate our proposal, we present a use case where the platform navigates through an orchard, collecting time-series data on fruits, using an RGB camera. The results from simulation and field experiments quantitatively evaluate the platform's scalability, accuracy, and dynamicity.**

***Index Terms*—Robotics, Agriculture, Digital Twin, Active Sensing, UGV, IoT**

I. Introduction

Precision agriculture is a data-driven approach to farming that uses information technology to collect and analyze data about crops, soil, and weather to improve agricultural productivity [1]. In the current global landscape of growing population and demand for food, climate change, and decreasing agricultural workforce, precision agriculture can help face these challenges by providing the tools to automate tasks, improve efficiency and work towards more sustainable agricultural practices [2].

In recent years, researchers have shown increased interest in the Digital Twin (DT) paradigm for precision agriculture [1], [2]. A DT represents a virtual replica or counterpart of a physical object, system, or environment. It uses high-quality models and simulations and high-resolution data to digitize the target. Here, DTs can help farmers better understand their crops, soil, and weather conditions, leading to better decision-making [1]. For instance, previous studies have reported using DTs for detecting plant diseases [3], forecasting yield production [4], and irrigation management [5], to name a few examples.

The Internet of Things (IoT) plays a pivotal role as one of the primary enablers of DTs. IoT involves connecting various devices, sensors, and actuators to a network, allowing them to communicate and exchange data. This vast network of interconnected devices provides a rich source of real-time data from the physical world, enabling the development of DTs [1], [2].

IoT installations for precision agriculture have grown significantly, but challenges remain. These installations require regular monitoring while facing power and connectivity limitations, increasing costs and restricting scalability [6]. Furthermore, fixed IoT installations may miss important changes in soil, crops, or weather patterns, limiting their adaptability [7]. Using unmanned aerial vehicles (UAV) with advanced imaging sensors provides a dynamic alternative [8]. However, drones face several constraints, including costs, flight time endurance, and payload capacity [9]. Thus, there is a need for a more adaptable, scalable, and cost-effective approach to monitoring agricultural fields.

This paper proposes a platform combining an Unmanned Ground Vehicle (UGV) with a Modular Sensing Payload (MSP) for active (i.e., dynamic and adaptable) sensing farming fields. The UGV is a compact rover suitable for outdoor terrains that leverages standard robot localization and navigation techniques. Its larger payload capacity distinguishes it from typical UAVs, enabling the integration of different sensing technologies (e.g., imaging sensors and environmental sensors). One key aspect of the proposal is integrating a robotic arm into the MSP. With this component, the platform can replicate fixed IoT installations and create a time-series dataset of a predefined region of interest (ROI). Furthermore, by leaning on Egde AI and distributed learning techniques, the sensing payload can adapt to the changing environment to improve data acquisition, for instance, by detecting new ROIs.

Compared to traditional IoT installations, our approach provides dynamicity and adaptation to data acquisition while increasing scalability and lowering costs, as one platform could survey several farms. To validate our proposal, we designed a simple use case based experiment where the platform navigates an orchard and collects time series data on fruits using an RGB camera. We evaluated the platform's scalability, accuracy, and adaptability within the experiment.

The rest of this work is structured as follows: Section II summarizes related works. Section III describes our proposed system. Section IV describes the ongoing experiments that aim to evaluate the goodness of our proposal. Section V finalizes the paper with the conclusions and future works.

II. Related works

There has been a growing interest in the Digital Twin paradigm for precision agriculture systems, as shown by surveys such as [1] and [2]. DTs can enable farmers to create a virtual replica or counterpart of their physical assets to make data-driven decisions. Authors in [3] used DTs to monitor plant health using image analysis algorithms and machine learning techniques. Farmers can detect early signs of diseases or pest infestations by continuously analyzing images captured by sensors or cameras, enabling timely interventions to minimize crop damage. Correspondingly, authors in [4] used DTs for yield production forecasting based on historical data, environmental factors, and predictive modeling. This approach enables proactive planning, optimal resource allocation, and effective supply chain management. Similarly, authors in [5] integrated data from soil moisture sensors, weather forecasts, and crop water requirements to create a DT. The objective was to optimize irrigation schedules and precisely deliver water to the crops when and where it is needed most. Nonetheless, there are still some challenges that need to be addressed in order to realize the potential of DTs in agriculture. One of the most important is related to data sources, with IoT being one of the main enablers [1].

IoT installations in precision agriculture have increased significantly over the past few years [2]. Nonetheless, several challenges are associated with these installations, which become constraints for enabling DTs. From the data acquisition perspective, these limitations can be summarized as follows:

- **Scalability and Costs:** Fixed IoT installations can be difficult to maintain, requiring regular monitoring while facing power and connectivity constraints [8]. These factors might increase the costs of the IoT system, limiting the number of installations and, thus, reducing the number of data sources for the DTs.
- **Accuracy and Reliability of the data:** IoT sensors are susceptible to various factors that can compromise the integrity of the data. Environmental conditions (e.g., temperature, humidity, and electromagnetic interference) can introduce measurement inaccuracies. Additionally, the complexity of IoT systems and the potential for software bugs or hardware malfunctions can further undermine the reliability of captured data [6].
- **Dinamicity and Adaptability:** Fixed IoT installations in agriculture have limitations when it comes to capturing the dynamic nature of the landscape. Due to their stationary nature, they often fail to account for crucial variations in soil conditions, crop growth, and weather patterns across larger areas. [6], [7].

One alternative to address these shortcomings is using Unmanned Aerial Vehicles (UAVs) with advanced imaging sensors, such as multispectral or hyperspectral cameras [8]. These UAVs can capture high-resolution aerial imagery of crops and fields, providing a more dynamic source of information to the Digital Twin. For instance, UAVs have been used to monitor orchards using a vision-based approaches [9].

However, drones in precision agriculture still face limitations. Besides costs, two significant constraints are drones' limited flight endurance and payload capacity. The short battery life restricts the coverage area and the amount of data collected during a single flight [9]. Weather conditions, such as strong winds or rain, can also limit the usability and safety of drones. Furthermore, regulatory frameworks surrounding drone operations, such as flight restrictions, privacy concerns, and licensing requirements, can pose additional challenges for farmers and drone operators [8].

III. Proposed System

This paper proposes an Unmanned Ground Vehicle (UGV) combined with a Modular Sensing Payload (MSP) to create an active (i.e., dynamic and adaptable) sensing platform. Our proposal aims to overcome the limitations of IoT systems for enabling DTs in agriculture. Figure 1 shows the high-level architecture of the proposed platform.

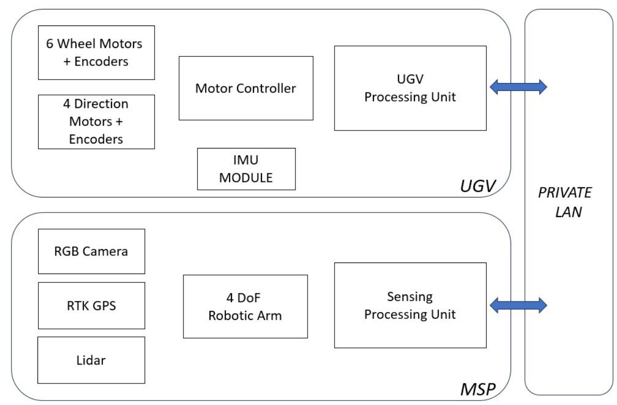


Fig. 1: High level diagram of the proposed active sensing platform.

The UGV is designed as a compact rover with six wheels, making it well-suited for autonomous navigation across various outdoor terrains. The hardware design is based on an open-source robotic project [10], while the software is developed using ROS [11]. The selection of open-source platforms for hardware and software reduces the platform's cost and allows customization and flexibility. Furthermore, selecting this UGV allows a significantly larger payload capacity than typical UAVs, enabling seamless integration of diverse sensing components.

The method for addressing the localization of the mobile platform is the Extended Kalman Filter (EKF) modeled using a unicycle-like robot kinematics [12], which enables the autonomous navigation of the UGV. The EKF incorporates three measurement sources: Real-Time Kinematic (RTK) GPS, an Inertial Measurement Unit (IMU), and a two-dimensional lidar sensor. The robot's position and orientation can be estimated relative to a reference frame in a local field map by fusing these sensor inputs. Furthermore, the navigation aspect of the mobile robot is accomplished through the integration of a Pure Pursuit controller [13] and a Hybrid $A^{\star}$ path planner [14]. The

Pure Pursuit controller enables smooth and accurate trajectory tracking by steering the robot towards a desired path based on its current position and orientation, and the Hybrid A* path planner facilitates efficient global path planning. To ensure obstacle avoidance during navigation, the proposed planner utilizes the lidar sensor and the field's local updated map. The proposed method's effectiveness and performance will be evaluated through simulations and experiments (Section IV). The results are expected to demonstrate a sensibly accurate performance for the employed localization and collision-free navigation system.

The MSP is designed to include various technologies for image capturing (such as RGB, ToF, and 3D cameras) and environmental measurements (such as luminosity, humidity, and temperature), easily adapting the platform for different use cases. By leveraging the versatility of these modular components, the UGV can autonomously and accurately capture real-time data from the farming fields it traverses.

One key feature of our proposal is incorporating a 4 DoF robotic arm into the MSP. By adding an RGB camera as the end actuator of the robotic arm, the platform can replicate different camera positions, gathering periodic samples with accuracy regarding location, focus, and position. Moreover, our platform leverages the capabilities of Edge AI and distributed learning paradigms, adapting to the changing environment to ensure the quality of the collected data. The sensing processing unit can perform real-time processing and analysis of the captured data, enabling the extraction of valuable insights and features directly at the network's Edge. Here, Edge AI empowers the UGV to make intelligent decisions, such as identifying and classifying objects of interest, detecting anomalies, or performing local data fusion, dynamically adapting to the changing environment. Furthermore, the Edge AI paradigm could be further extended to take advantage of distributed learning paradigms, creating a distributed network with other processing units, such as IoT installations or other UGVs.

Therefore, leveraging the technologies mentioned above, our proposal presents a novel approach to enable DTs in agriculture. Compared to traditional IoT installations, our approach provides dynamicity and adaptation to data acquisition while increasing scalability and lowering costs, as one platform could survey several farms. Figure 2 shows a picture of the proposed platform prototype.

Fig. 2: Prototype of the UGV platform with a modular active sensing payload

IV. Experimental Evaluation

To validate and evaluate the goodness of our proposal, we designed a simple use case based experiment: The platform navigates through an orchard and collect time series data on fruits, using an RGB camera as the mobile sensor attached to the robotic arm. The UGV is programmed to move between tree rows autonomously, reaching predefined waypoints to capture images using visual fiducial markers as references (i.e., ArUco markers [15]) . Here, the markers indicate one or more regions of interest (i.e., fruits), translating into different poses for the robotic arm to capture RGB images. Finally, this entire process is repeated several times to create a time series dataset. This experiment focuses on three factors derived from the limitations identified in Section II: scalability, accuracy, and dynamicity. The platform's capability to navigate predefined paths to reach visual markers autonomously validates the platform's scalability. The accuracy is measured by comparing the angle, distance, and orientation of the pictures taken of the same region of interest. Finally, the adaptability of the platform by measuring the precision of fruit detection using state-of-the-art vision Edge AI algorithms (e.g., MobileNetV2 [16]) running on the sensing processing unit. Simulation results are briefly described in section IV-A, while field results are presented in section IV-B.

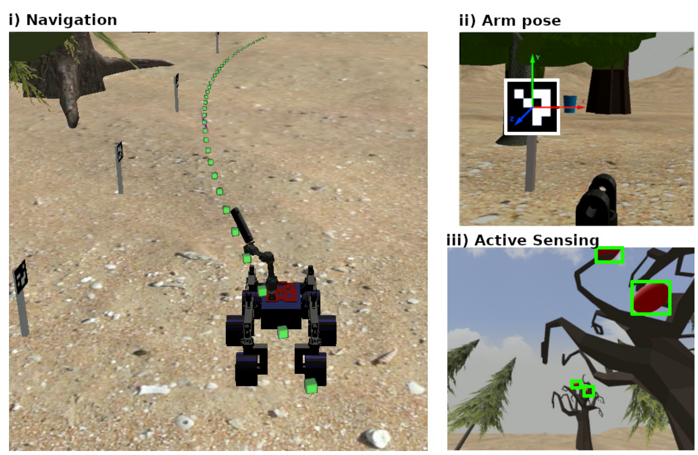
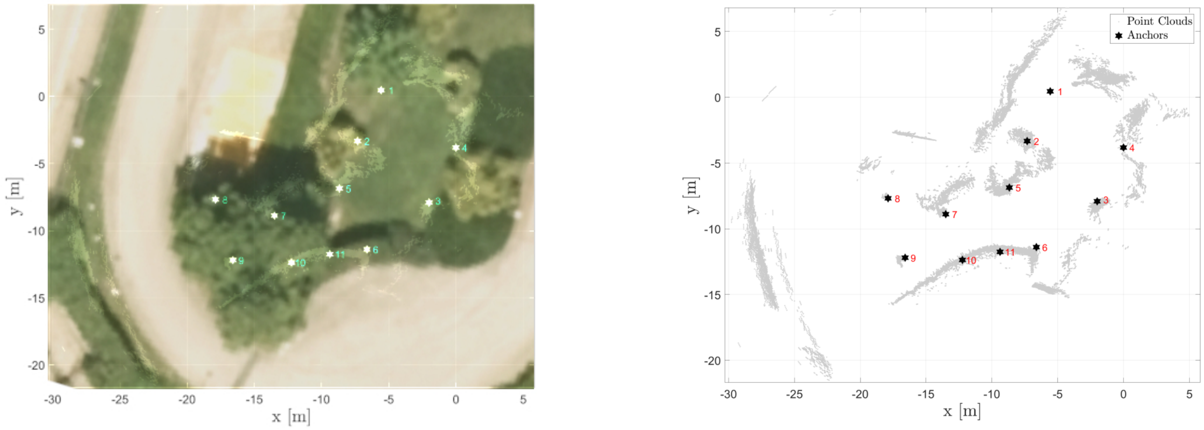


Fig. 3: Three phases of the simulated experiment: Navigation, Arm Pose, and Active Sensing.

A. Simulation

The virtual world (using the Gazebo simulator) represents an agricultural landscape, including fields, orchards, and other features commonly found in farming scenarios. By placing the markers in different locations, the scenario aims to test the platform's ability to navigate these markers autonomously using perception and localization algorithms and the ability of



(a) Orthoview of the terrain using an open data satellite image

(b) Occupancy map generated with the on-board sensor

Fig. 4: Overview of the location for the outdoor field experiment.

the arm to replicate predefined poses based on the markers. The simulation scenario consists of three distinct phases: i) Autonomous Navigation: In this phase, the rover platform is tasked with autonomously navigating to the locations of the markers. The platform utilizes onboard sensors (i.e., GPS, LiDAR, IMU, and odometry) to perceive the environment and plan collision-free paths. The successful completion of this phase demonstrates the platform's ability to traverse the simulated agricultural world autonomously, highlighting its scalability as a data collection tool; ii) Arm Pose Adjustment: Upon reaching an ArUco marker's vicinity, the platform adjusts its robotic arm's configuration to focus on specific ROI (e.g., apples in a particular tree). This phase tests the platform's robotic arm's capability and ability to position the camera or sensor for data collection precisely. The comparison of different captured RGB images of the same ROS validated the platform's accuracy. iii) Active sensing: Once the sensor is positioned for data collection, the platform performs additional active sensing tasks besides taking the sample (i.e., the RBG image). The object detection algorithm analyzes the image to identify and count the number of fruits. The successful detection of fruits within the specified regions of interest showcases the platform's dynamicity and adaptability for active sensing. Figure 3 shows the three simulation phases.

B. Field

The use case was implemented in an outdoor terrain covering approximately 250 square meters. Substantial tree coverage introduced varying signal obstruction for GPS reception within this terrain. The topography featured a two-meter elevation change, ranging from the lowest to the highest point. As references for the environment, figure 4a shows a 2015 orthoimage available as open data from the municipality of Trento [17], and figure 4b shows an occupancy map generated by the on-board lidar sensor.

To overcome the limitation of the GPS signal, we strategically positioned 12 UWB anchors at various locations, ensuring comprehensive coverage. These anchors are a cost-effective solution for positioning and navigation, as described in [18]. In our setup, these markers provided positioning with an accuracy of 10 cm. We defined a safety area for the robot to work, and within this area, we marked two different ROIs (i.e., plastics apples on trees). Figure 5 shows the position of the anchors on a map, a picture of the location of three UWBs, and a picture of one of the ROIs.

In this field, the robot autonomously navigated to each ROIs with a 0.5m radio of precision. At each ROI, the robot positions the arm and captures a picture using a 12MP portable RGB camera. We repeated this process several times and created a time-series dataset of 100 pictures for each ROIs. For evaluating our approach of active sensing using Edge AI, we tested two different object recognition algorithms, MobilNetv2 [16], and FoMo [19] (an optimized variation of MobilNetv2). These algorithms are selected based on current literature on Edge AI object detection using constrained devices (e.g., [20]). Each algorithm was trained using transfer learning over our datasets, which were manually labeled to identify the apples in the picture. The dataset was split into 80% for training and 20% for testing, where 20% of the training pictures were used for validation. The image pipeline consisted of cropping the image to a square, resizing the image to 320x320, and then training with 60 epochs using a learning rate of 0.001 over 307200 features (RGB). Table I shows metrics of the algorithms, including the F1 precision score and the performance on the onboard sensing unit (i.e., a Raspberry Pi-4 SoC). It is important to notice that evaluating other object detection algorithms and fine-tuning the parameters for better accuracy is beyond the scope of this paper.

The results from this field experiment campaign validate the benefits of our proposal in terms of scalability, accuracy, and dynamicity. Regarding autonomous navigation, the platform reached each ROI despite the diverse conditions of the terrain (e.g., type of soil, humidity, slope). Furthermore, even with conservative parameters for the localization accuracy (0.5m

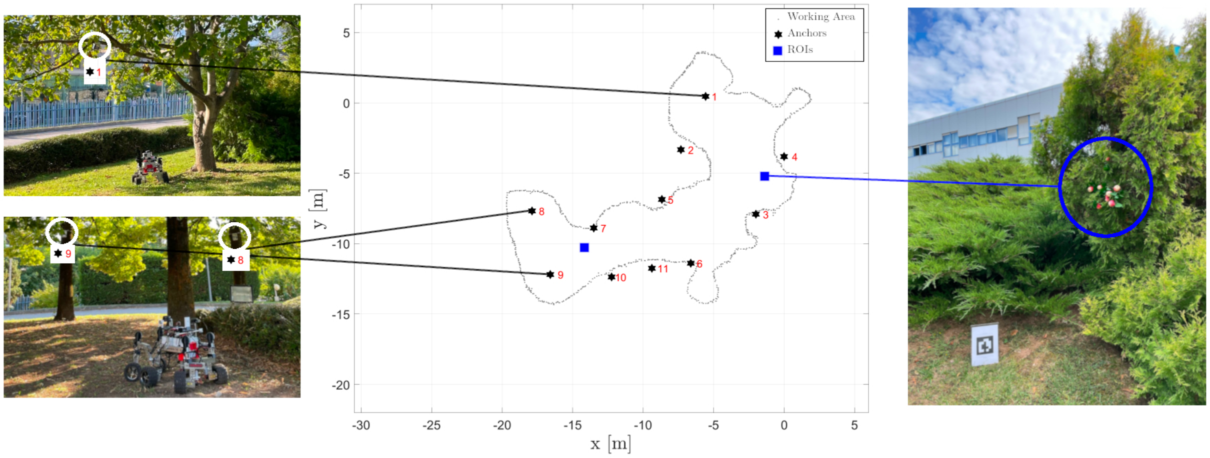


Fig. 5: Experimental setup for the field experiment: At the middle, the UWB anchors position and the safety working zone. On the left, two images showing the locations of anchors 1,8, and 9. On the right, a picture showing the ROI-1 setup.

	FoMo	MobilnetV2
F1 Score	85 %	75 %
Memory Usage	65 KB	11 MB
Inference Time	50ms	450ms

TABLE I: Comparison of 2 different object detection algorithms over the collected datasets from ROI-1 as an example of active sensing on the robot

radius) and velocity (0.2 m/s), as well as the limitations of the current platform prototype (e.g., the precision of the odometry), the rover completed the data collection in a matter of minutes. These results highlight the scalability of our solution, as it would autonomously create a time-series dataset with high granularity for several ROIs and can be used in more than one farm.

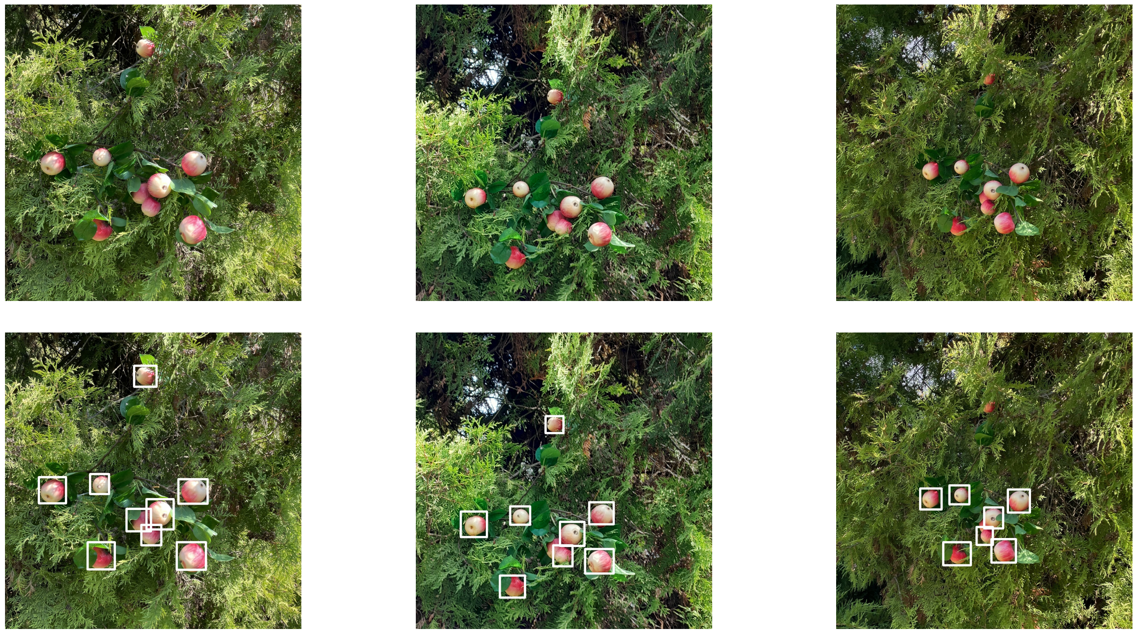
Concerning the arm pose adjustment, the platform successfully adjusted its robotic arm's configuration to precisely focus on specific regions of interest. As shown in Figure 6, images in the dataset exhibit a high degree of visual similarity in terms of location, focus, and position, demonstrating the accuracy of our approach. This high-quality dataset reduces the efforts and costs of acquiring, categorizing, and annotating images, key elements for more complex analytical tasks [21].

Regarding the active sensing phase, once data has been collected (i.e., picture taken), the platform performs a straightforward Edge AI object detection task. Using an onboard algorithm (i.e., FoMo), it analyzes these images to recognize and count the number of fruits within the frame, achieving high speed (e.g., just a few milliseconds) and minimal resource consumption (only a few megabytes of disk space) on the sensing processing unit. Notably, the platform successfully identifies and labels apples with an average accuracy of 85% using just a state-of-the-art algorithm without further refinements. This simple active sensing example holds the potential to enhance the data collection process significantly. For instance, the system can automatically adjust the arm to capture more images in a single location. Consequently, these additional images can uncover new regions of interest, effectively addressing the dynamic nature of agricultural environments, such as obscured fruits due to leaf cover or changing light conditions.

V. Conclusions and Future works

In this paper, we propose a platform for active sensing in outdoor fields, facilitating the exploration of the Digital Twin Paradigm in agricultural applications. The platform is based on a UGV combined with an MSP, enabling autonomous navigation across diverse outdoor terrains and offering a larger payload capacity than traditional UAVs. By integrating a robotic arm into the MSP, our platform achieves precise time series data collection and adapts to dynamic environmental changes. Additionally, our approach increases scalability and lower data collection costs, as one platform could survey several farms. To validate our proposal, we presented a use case based experiment where the platform navigates through an orchard collecting time-series data on apples, using an RGB camera as the main sensor. Our experimental results confirmed our proposal's scalability, accuracy, and adaptability. The platform autonomously navigated through diverse environments, completing data collection in just a few minutes. It adjusted its robotic arm precisely, creating accurate time-series datasets of different ROIs. Furthermore, with simple on-board object detection capabilities, it achieved an 85% accuracy in detecting and labeling apples using minimal resources. This simple active sensing process enhances data collection in dynamic agricultural settings, highlighting our proposal's potential for enabling agricultural Digital Twins.

Future works include implementing different use cases for the platform, such as 3D models of ROIs, and exploring different Edge AI tasks for improving active sensing, such as increasing the precision of the object detection task.



(a) 100% (9 of 9 apples detected) (b) 88% (8 of 9 apples detected) (c) 77% (7 of 9 apples detected)

Fig. 6: Sample images from the ROI-1 time-series dataset (top) and object detection with its accuracy on the sample images (bottom).

ACKNOWLEDGMENT

This work was partially supported by the AI@TN project, funded by the Autonomous Province of Trento, and by the Interconnected Nord-Est Innovation Ecosystem (iNEST), founded by European Union Next-GenerationEU (PNRR, Missione 4 Componente 2, Investimento 1.5 – D.D. 1058 23/06/2022, Ecs00000043).

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