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A Mobile Robot with Deep Learning for Monitoring Coffee Farms

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Abstract*–Coffee is one of the most important products for Honduras, not only due to the amount of exports, but also its importance in the national value chain. The main objective of this project is to develop a rover to monitor coffee farms for rust detection. The robot consists of different subsystems: the first is to collect images to train the neural network, and the second is to monitor the coffee farms. The third subsystem, the Web subsystem, describes the challenges of wireless communication in coffee farms, detailing the characteristics of the hardware and the network configuration required to achieve such communication. The mechanical subsystem was developed based on a simulation model that was tested in different scenarios to ensure its operation in the coffee farm. It also describes the algorithms to mobilize the robot, including the detection of possible collisions and the proposed algorithm to avoid these collisions. Finally, the prototype and its limitations are presented to develop its work in coffee farms in Honduras.

Keywords-- Coffee farms, Honduras, Mobile structures Robotics, Rust detection

I. INTRODUCTION

Latin America has countries that are fully dedicated to coffee cultivation, led by Brazil and Colombia, which are ranked number one and three worldwide, respectively. Colombia, one of the largest coffee exporters, can influence the prices of countries with lower exports, such as Honduras [1]. Therefore, countries with lower export capacities should take steps to modernize their coffee farms [2]. This modernization will help reduce the costs of coffee production, thus increasing the income of the owners.

The price of coffee fluctuates and is difficult to predict, making coffee a highly risky investment. In the coffee value chain, various stakeholders participate, including producers, intermediaries, cooperatives, and exporters. All of these intermediaries play a crucial role in the economic development of coffee-producing countries. For instance, cooperatives facilitate intricate processes that offer significant benefits to rural communities, encompassing training, employment opportunities, and services aimed at advancing the post-harvest coffee processes. As most suppliers exert an impact on the environment and the community, ongoing evaluation of their activities is imperative [3]. Nevertheless, within this value chain, the primary and most pivotal actor is the producer, who sustains the economy of rural areas. Producers serve as the key contributors to the vitality of the coffee economy, contending with international price fluctuations and the threat of rust. Hence, the development of innovative methods for the modernization of coffee farms becomes a necessity [4]. As an illustrative instance of technology implemented in coffee farming [5], two decision tree methods were compared for the early detection of coffee rust: a fuzzy model and a classical model. Fuzzy and classical decision trees were induced for all datasets. In recent years, technology development has been steadily advancing, particularly prior to the onset of the pandemic.

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Currently, there is a large amount of research on coffee, robotics, and artificial intelligence [5]–[15]. Coffee farm-oriented robots are uncommon in underdeveloped countries. This is largely since coffee-producing countries are not highly technological. The countries that have more developments in this area are Brazil and India, but, as mentioned above, these countries do not invest heavily in technology due to the fluctuating coffee market. There is currently no evidence of robots being used on coffee farms for monitoring rust [7] and coffee beans [8]. Therefore, a rover that can monitor coffee farms is a necessity in the agricultural sector of coffee-producing countries.

II. DESIGN METHOD

The V-method requires the subdivision of subsystems for clear integration based on the various systems required for the product. It precisely outlines how to address distinct product cycles, transitioning the design from a conceptual idea and a prototype to the production of the product. The breakdown of the coffee rover subsystems facilitated the development of the robot. However, each designer can suggest different ways to realize projects like this one. Therefore, the use of this methodology does not define the only path to follow for the development of coffee-oriented robots but rather the steps that allowed the development of this project.

This methodology, in addition to decomposing a complex mechatronic product such as a robot into systems and subsystems, allows for the development of product cycles, where a finished product is not expected to be obtained in the first cycle. In this project, two V development cycles were performed. The first cycle is based on simulated prototyping of the robot to ensure its operation, and the second is based on manufacturing and field testing to obtain a functional product. Figure 1 shows the systems and subsystems proposed for the development of the functional prototype.

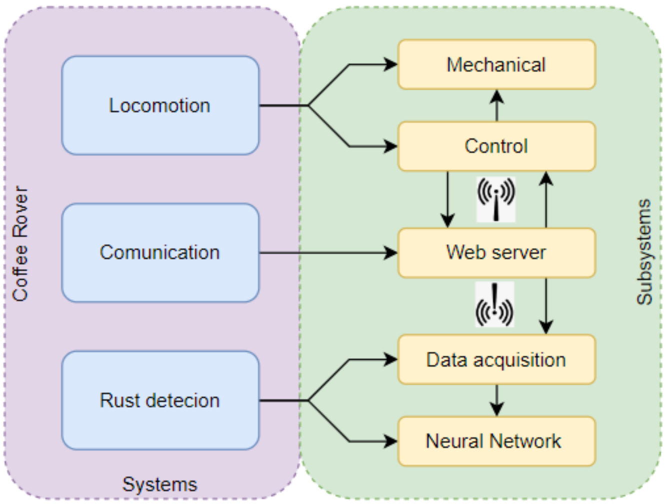

Fig. 1: V method systems and subsystemas

III. Development

The results of the development of each system and subsystem implemented to make the robot capable of working in the coffee farms are shown below. For this purpose, the results section is divided into five subsystems and a final section of integration and testing.

The mechanical subsystem presents everything related to the structural design of the robot, simulations, and manufacturing of the structure. The mobilization subsystem describes the operation of the robot movement algorithms, including collision detection. The Web subsystem presents the challenges of wireless communications in coffee farms, describing the characteristics of the hardware and the network configuration to achieve such communication.

The data detection subsystem explains the process by which the robot can take images of the rust for further analysis. The rust detection subsystem explains the steps and technologies implemented to detect rust and is compared with other proposals from other researchers. Finally, the finalized prototype and its limitations to develop its work in coffee farms in Honduras are presented.

A. Mechanical Subsystem

The design of the structure was tested to withstand shocks and the weight of the electronic components. The robot's design features a structure different from the configurations typically used in robots. The rear tires were positioned towards the end of the robot to provide balance, while the front tires were placed towards the center to ensure that the front and rear tires encounter different obstacles, thereby preventing the robot from becoming stuck as it moves across terrain.

Tension tests were conducted by placing a 200 N weight on the robot structure, with the tires acting as support. Figure 6 illustrates that the red area represents the region of highest displacement in the robot structure, with a mechanical displacement of 0.344 mm, which is negligible. This indicates that the structure is sufficiently rigid to withstand the suggested weight. As for the robot's sides, a maximum displacement of 0.296 mm is expected, which should not pose any issues for its development. No critical breaking points were observed in the von Mises simulation.

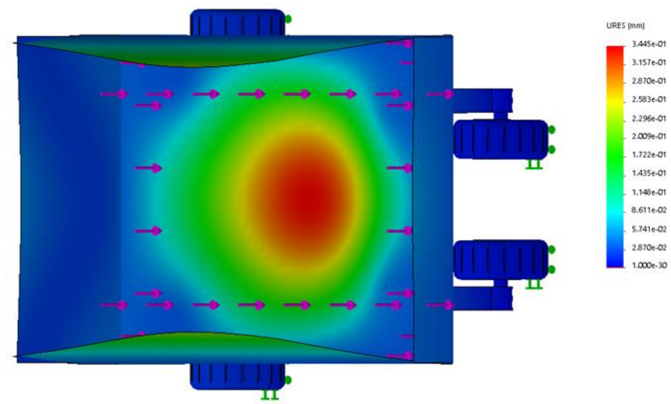
Fig. 2: Rover structure tension simulation

The structure was designed with triangular aluminum supports, and TPU tires were designed to facilitate mobility on unstable terrain. Therefore, a surface with rocky characteristics was developed to simulate the robot's movements, as shown in Fig. 3. The stage is 4 meters long to accommodate the path, with circular obstacles of 120 mm and 80 mm placed around the surface, and an elevation of approximately 5 degrees. For this, two simulations were developed. In the first one, the four motors are set with an angular velocity of 100 rpm, a gravity of 9.8 m/s, a weight of 200 N, a static friction coefficient of 0.1, and a kinetic friction coefficient of 0.15.

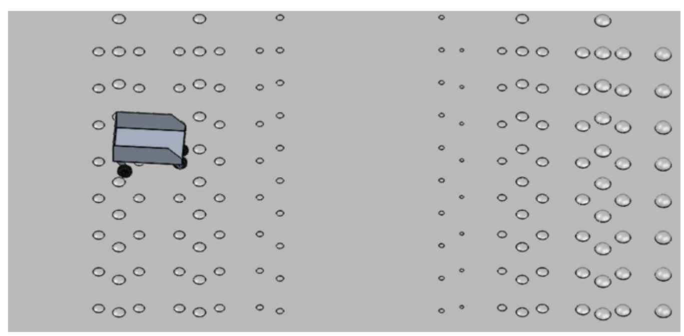
Fig. 3: Rover obstacle simulation

In the first scenario, the robot moves across the stage, overcoming various obstacles along the way. The total displacement exceeded 7.5 meters, with a maximum velocity of 657 mm/s achieved. When the tires directly impact the obstacles, the linear velocity decreases, as depicted in Fig. (4) by the red graph and its descending peaks. These velocity fluctuations lead to constant changes in acceleration, which significantly influences the choice of battery.

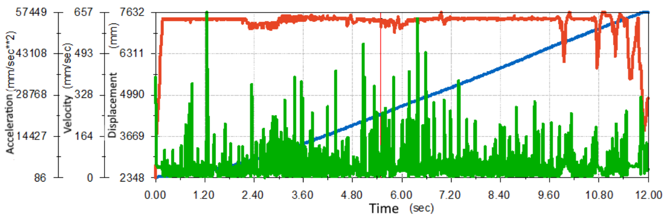

Fig. 4: Simulation result: displacements (blue), velocity (red) and acceleration (green)

The behavior of the robot's rear-wheel drive is now analyzed. Figures 5 and 6 depict the torque required for the rover to cross obstacles. The variations in torque are attributed to the force required for the motors to overcome the obstacles. According to the simulations conducted, front-wheel drive requires more torque than rear-wheel drive. This is attributed to the front drives experiencing more impact from the obstacles in the scenario. The maximum torque achieved was 5582 N-mm, with these torques increasing as obstacles are encountered. This is because a vehicle moving on flat surfaces would require less torque for mobility.

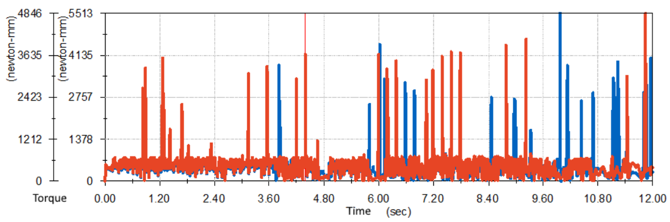

Fig. 5: Front wheels torque

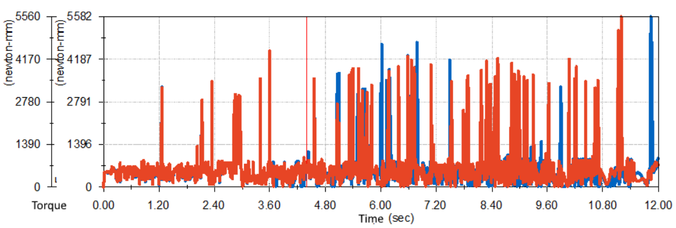

Fig. 6: Back wheels torque

In the second simulation, we analyzed how the robot turns to the right and left. Initially, the motors on the right side were given angular velocity, while no velocity was applied to the motors on the other side. However, the robot moved linearly without rotating, prompting a repeat of the test. This time, the motors were moved in the opposite direction, resulting in a rotation to the right. The rotation of the robot is not circular due to the position of its wheels; instead, it exhibits an undulatory motion. Figure 7 illustrates the kinematic behavior of the robot, highlighting the changes in angular velocity that allow the robot to turn at 47 deg/s. This rover follows an undulatory trajectory, which can be described, with some limitations, as the concave part of a polynomial of degree 2.

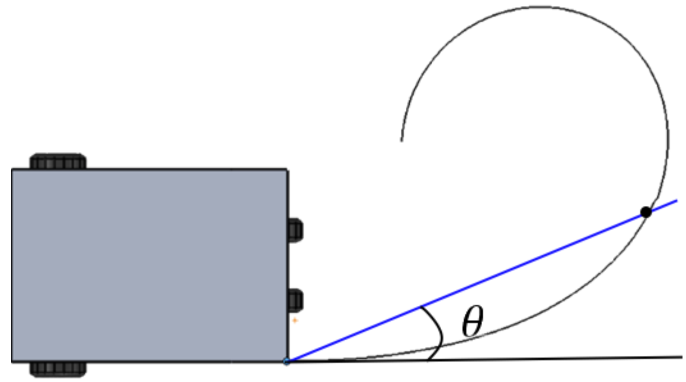

Fig. 7: Robot variable floating point

In the case of the simulation, all the path points of a corner of the robot structure were extracted to develop a polynomial regression. This resulted in equation (1), which has a reliability greater than 98%.

$$y = 0.0002x^2 - 0.041x - 3076.1 \tag{1}$$

Regarding the angular momentum generated by the robot during its undulatory movement, it is observed that while the robot moves linearly, the angular momentum is very close to zero. As the robot initiates its movement, this angular momentum gradually increases, and it has been noted that obstacles hinder these turns. Figure 8 illustrates the behavior of the angular momentum as the robot traverses the scenario. Based on these simulations, it is shown that the robot's structure is viable for complex surfaces such as those found in coffee farms.

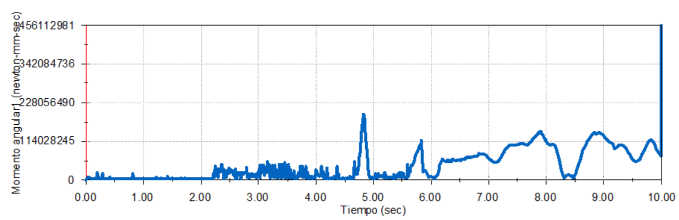

Fig. 8: Wheel for prototype

The manufacturing of the tires was one of the most important challenges. For this, we utilized TPU for the tires and PLA for the rims, as depicted in Fig. 9. The printing time for each tire was approximately 18 hours, while it took 12 hours for the rims. A 15% infill was incorporated into the tires to enhance their elasticity, enabling them to better overcome obstacles in the coffee farms. This design was based on the one proposed by [16], where the advantage of cutting the wheels to overcome obstacles is demonstrated.

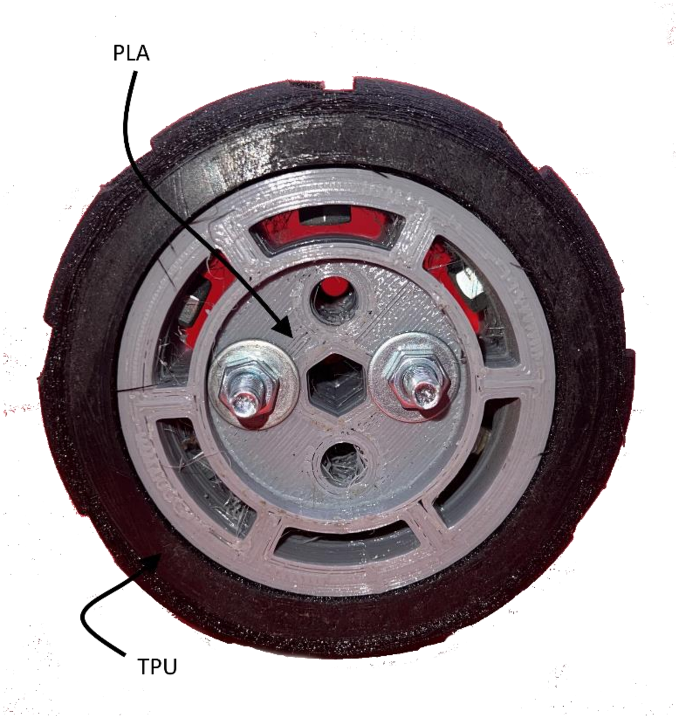

Fig. 9: Wheel for prototype

For the robot's manufacture, we utilized a 4 mm aluminum sheet bent to size to support the angular moments and securely hold the electronic equipment in place. Triangular supports were attached using screws to accommodate the motors, ensuring stability and proper positioning. To ensure high torque, motors with gearboxes operating at an angular speed of 80 rpm and 12V were carefully selected. The motor couplings for the rims were integrated during the manufacturing process, and various structures were tested to validate the actuators' operation. The mechanical subsystem was developed based on a simulation model that underwent testing in different scenarios to ensure its functionality in coffee farms. However, certain parts of the original structure were cut to reduce weight, thereby decreasing torque and enabling lower energy consumption. Adequate space was allocated for installing the electronic equipment and the vision system essential for the robot's operation.

B. Control subsystem

The controller features a web server accessible wirelessly. A significant advantage is the implementation of radio frequency compatibility with these devices, increasing scalable opportunities as shown in Fig. 10. For motor control, three relays are utilized: one to regulate the current flow to the motors (K3) via an open contact, and the other two to control the motors on the left side (K2) and right side (K3), respectively. To move the robot forward, it is only necessary to activate K3; for backward movement, K3, K1, and K2 must be activated. Finally, to execute turns, activating K3 along with K1 for right turns or K2 for left turns is required. The relay set is connected to the PLC outputs (Q0.0, Q0.1, and Q0.2), which will be controlled through a web service interface.

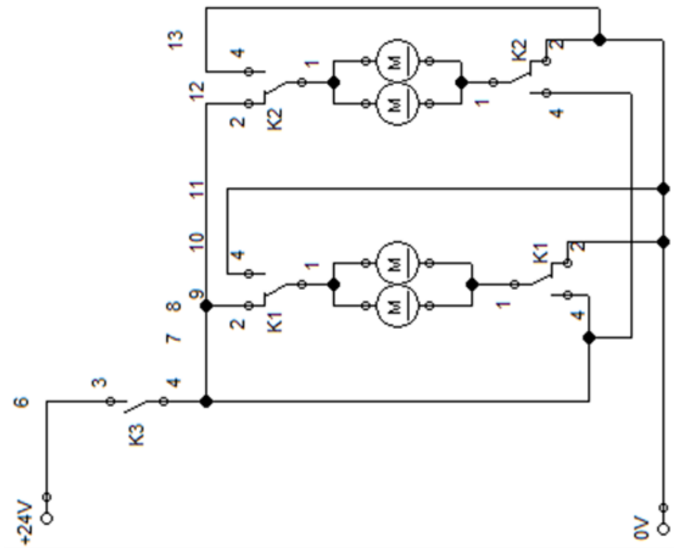

Fig. 10: Motor control

For object detection, two digital sensors are positioned on the front of the robot, one on the right and one on the left. One of the sensors is configured to detect collisions within a 30 cm distance, while the other is set to detect collisions up to 180 cm away. If the 30 cm sensor detects an obstacle, the robot will come to a stop. If one of the 180 cm sensors detects an obstacle for at least 0.5 seconds, the robot will execute a sequence of actions: it will turn in the opposite direction for 0.5 seconds, move forward for 0.5 seconds, and then turn for 0.3 seconds to correct its path. In the event that both 180 cm sensors are triggered simultaneously, the robot will reverse for 0.5 seconds and come to a stop. In such cases, it will wait for manual intervention to proceed step by step. This precaution is necessary because coffee farms are typically narrow, making it impractical for the robot to autonomously correct its path under these conditions. The sensors are connected to the PLC through inputs I0.0, I0.1, I0.2, and I0.3 as illustrated in Fig. 11.

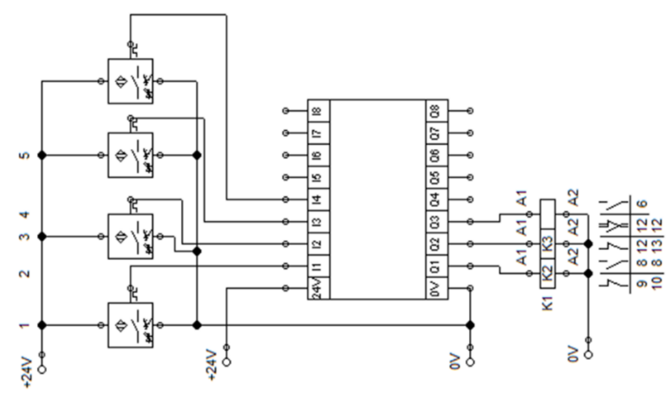

Fig. 11: Robot controller

To develop this system, several calculations were performed to estimate the reaction times of the robot. Based on the simulations, the robot moves at a speed of 6 m/s. Applying equation 2, the time for the robot to collide with an object at 1.8 m is calculated to be 0.3 s. Since it's possible that some objects are moving, the sensor must detect the object for at least 0.1s to confirm a collision. Therefore, the robot has a window of 0.2s to avoid collision. Figure 12 illustrates the block developed in SCL for collision detection.

$$t = d/v \tag{2}$$

According to the simulations, the maximum angular velocity of the robot is 47 deg/s, but on average it moves at 25 deg/s. By applying equation 3, the tilt angle can be calculated to avoid collisions. The robot rotates approximately 12.5 degrees to bypass the obstacle, then turns approximately 7 degrees to continue its path. When calculating the distance x from equation one using the tilt angle, an approximate value of 0.2m is obtained. This is the minimum distance the robot needs to successfully dodge the obstacle without considering its width.

$$\theta = w * t \tag{3}$$

The mobilization control subsystem is one of the most complicated aspects, given that the robot needs to be controlled remotely. Analysis and calculations are derived from data obtained in simulations, and tests were conducted to integrate the controller with the mechanical subsystem. The tests were conducted using 7500mA batteries at 12 V.

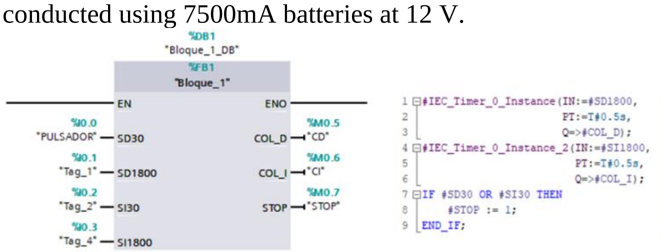

Fig. 12: SCL programming block

C. Webserver subsystem

The web server subsystem outlines the equipment utilized to establish a mobile wireless network. It's crucial to emphasize that in the coffee plantations of Honduras, establishing a wireless internet connection is often not feasible due to the rural nature of many locations. Therefore, a local point-to-point wireless network with a range of 1 km is proposed. To enable teleoperation of the robot in coffee farms, a controller capable of providing a web service was selected. For communication purposes, an omnitik antenna capable of point-to-point communication over a 180-degree outdoor range was employed. This antenna, besides facilitating wireless communication, features 3 Ethernet ports for establishing a LAN network to connect the Web Server and the IP camera. The IP camera is essential for teleoperating the robot as it allows for obstacle observation. For this purpose, a 2-megapixel HIK Vision camera was utilized.

The web interface was developed in Visual Studio Code using HTML language for the graphical aspect. When using the PLC S7 1200, the HTML code header of the web page must include the PLC variables. AWP is the language employed by the PLC. The forms should use the same variable names in the denominator as the variable name. Figure 13 illustrates the HTML test code for controlling the engines via the web. This code needs to be integrated with markers into the robot program rather than directly into the PLC outputs to enable robot control from various devices without affecting the collision detection subsystem. The forms operate independently for different robot operating states. These form buttons function as switches, meaning that when pressed, the signal remains active even after releasing the button.

```
<!DOCTYPE html>
<!-- AWP_In_Variable Name='"ENCENDER"' -->
<!-- AWP_In_Variable Name='"C_GIRO"' -->
```

Fig. 13: AWP for html headers

The HIK Vision camera is designed for outdoor use, making it suitable for environments with high humidity, such as coffee farms. Figure 14 illustrates the proposed scheme for establishing communication in coffee farms. Each unit is assigned a specific IP address to access the PLC web service. To access the web service, it is necessary to enter the IP address of the unit into a web browser on the PC. This architecture is known as point-to-point, where there is a control station and a mobile equipment operated from the control station. While it is possible to connect to the robot from the PC without the need for an additional antenna, it would require relocating the control station as the robot moves forward. According to the equipment manufacturers, the theoretical range is 1 km when using both antennas outdoors. Therefore, both antennas must be configured for outdoor use.

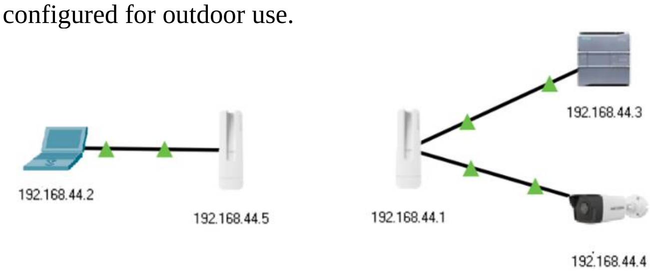

Fig. 14: Point-to-point communication

The wireless communication web system was tested using the two previously developed subsystems. Finally, this equipment is installed on the robot structure. The interaction time between the orders sent by the control station is approximately one second, highlighting the importance of collision detection to promptly stop the robot and prevent damage to both the farm and the robot.

C. Data acquisition subsystem

The data acquisition subsystem is carried out in two stages. The first stage involves acquiring images to train the neural network, while the second involves monitoring coffee farms. It is essential to use a high-resolution device for image acquisition, as utilizing images from the internet is not feasible. Data acquisition is facilitated by an external camera that captures images at set intervals until the required number of images is obtained. These images are stored in a single file and saved chronologically to simplify subsequent analysis.

A 16 MP 4K camera is selected for this purpose, equipped with a waterproof protector to shield it from moisture. A PVC support is installed to position the camera at a height of at least one meter, enabling it to capture images of coffee plants effectively. The camera is equipped with Bluetooth control for remote picture-taking. This control is connected to an output of the PLC S7-1200, with the robot responsible for initiating image capture. The control sequence is configured to capture images every 30 seconds, requiring the incorporation of a counter to determine the number of images to be captured by the robot. Figure 15 illustrates an example of image acquisition using the camera.

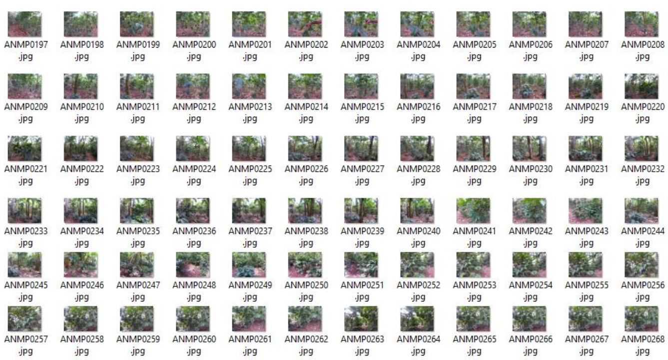

Fig. 15: Data acquisition example.

E. Deep Learning subsystem

The last developed subsystem is the rust detection subsystem; unlike the other subsystems, this one analyzes the images taken by the robot. This system is not integrated with the robot but utilizes the robot's data to analyze the amount of rust in each image. This section examines the training method and the neural network for rust detection.

The training was conducted using the Roboflow APP, with 500 images after augmentation, which were divided into 450 training images, 15 test images, and 15 validation images. Training was carried out over 240 epochs, resulting in an average accuracy of 76% across the three classes. The class with the lowest accuracy is that of rust; in the initial training, a smaller image filter was used, which made the detection of this class more challenging due to its size. Figure 16 depicts the implementation result of the neural network.

Fig. 16: Detections: rust (red), damage leaf (purple) and coffee beans (yellow)

IV. CONCLUSIÓN

This project introduces a new method for monitoring coffee farms at the design level. The rover (Fig. 17) is equipped with certified industrial equipment, ensuring a high degree of reliability in performing its tasks. In the simulation, we presented a terrain with various slopes and obstacles resembling those found in a typical coffee farm. The wheel configuration was meticulously designed to reduce the likelihood of the robot getting stuck, a critical feature given the terrain's irregularities. These wheels are 3D-printed using TPU to dampen the impact of terrain irregularities, providing smoother and more effective robot mobility under real field conditions.

While the robot's primary function is to monitor rust, it became evident that there is a genuine need to automate and develop new methods for farm maintenance. This innovation may be particularly appealing to the new generation of young coffee growers, potentially deterring them from migrating and leaving the family business. The rust detection system demonstrated an accuracy rate of over 75% in its operations. However, obtaining concrete results regarding the harvest necessitates monitoring the coffee farm for more than a year with the proposed robot. Additionally, farm layouts must be improved by clearly defining pathways that allow the robot to comprehensively monitor the entire farm. A new type of wheel with legs also should be part of the solution [17].

Currently, the forefront of technological development in the agribusiness sector is led by countries like Brazil and India. Therefore, it is imperative to establish policies that encourage the establishment of companies in this field and even consider providing certified versions of projects of this nature to promote technological advancements in the sector.

Fig. 17: Rover prototype

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