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Original Article

Development and Control of Drones Applied to Monitoring in Fruit Growing during the Harvesting

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Abstract - *In the agricultural industry, accurate and efficient monitoring of the state of crops during the harvest stage is essential to ensure the quality of fresh produce, so this work proposes a system for monitoring fruit at the harvest stage through the use of drones and the development of image processing algorithms to estimate the measures of the fruit by comparing stereo vision and ArUco Marker; in addition also develops an algorithm to specify the stage of maturity in which they are. The tests were carried out on avocado crops in the Majes valley, Arequipa. In the tests, the effectiveness of the algorithms was obtained, evaluating the data obtained by the system and the actual data, demonstrating a reliable detection and an accurate calculation of the size of the avocados. The results are visualized by means of maps highlighting the different stages of maturity. This innovative approach presents significant potential for improving crop monitoring and management, especially in regions such as fruit exporting in Arequipa, where quality and precision are crucial to consolidate its position in international markets.*

Keywords - *Image processing, Agricultural monitoring, Drone technology, Stereo vision, Measurement estimation.*

1. Introduction

As the demand for fresh, high-quality produce continues to grow, it is becoming increasingly important to have highly efficient and accurate monitoring methods to assess the condition of fruit orchards during the harvest stage. This period is crucial, as it largely determines the quality and quantity of the production that will reach the market. Traditional manual visual inspection approaches, while widely used, present a number of significant challenges. First, they are often costly, requiring the hiring of skilled labour, which increases operating expenses for growers. In addition, manual inspection can be a laborious and time-consuming process, limiting the ability to assess large areas of crops efficiently.

Another aspect to consider is the limitation in terms of the range and accuracy of traditional methods. Humans, however trained, have physical and attention limitations that can lead to the omission of essential details or lack of consistency in fruit assessment. In the face of these challenges, the adoption of advanced technologies, such as computer vision and automation through drones and image processing systems, emerges as a promising solution. These technologies enable the rapid and accurate capture of data on crop conditions, including the detection of ripe and unripe fruit and their size. By reducing costs, increasing speed and improving accuracy, these innovations are revolutionizing the way fruit fields are monitored during harvest, providing growers with an invaluable tool to optimize their operations and meet the growing demand for high-quality agricultural products. For this reason, drones have emerged as a promising solution for agricultural monitoring, offering the ability to capture high-resolution aerial images and provide detailed information on plant conditions and crop yields. The development and control of drones applied to fruit crop monitoring during the harvest stage presents significant challenges in the agricultural industry. According to the official SENASA report, the primary exportable fruit of the Arequipa region, Peru, is grapes, followed by avocado and pomegranate; these products have had significant growth in exports in recent years.

Due to the quality of the production and the condition of the eradicated area of fruit flies, agro exports to crucial markets such as Holland, China, the United States, Spain, and other international destinations have been consolidated. Therefore, this article aims to explore and evaluate the feasibility and effectiveness of a system using controlled drones to patrol fruit orchards, perform image processing and issue sectoral alerts on fruit maturity. Through data collection and experimental tests, the aim is to demonstrate the effectiveness of this technology and its potential to improve the monitoring and management of fruit crops during the harvest stage. In addition, in order to support the farmer and thus avoid losses such as fruit spoilage due to lack of harvest.

This document is divided as follows: The related works are presented in section 2, and the methodology is presented in section 3. section 4 describes the development of the system proposed; the drone stage subdivides this section, along with the algorithm developed and the control station. section 5 presents the test and results obtained. Finally, section 6 presents the conclusions of the research.

2. Related Works

In the existing literature review for the improvement of automated fruit harvesting, a method is presented in [1] that uses RGB images to estimate the position of citrus fruits. Using the FPENet model, high accuracy in navel point detection and fruit rotation vector prediction is achieved, with 79.79% harvesting success. In [2], a bottom-up approach for 2D position estimation of multiple tomatoes with peduncle is proposed, highlighting its high performance in crucial point and distal peduncle detection, which promises applications in robotic harvesting and harvesting priority determination. The evolution of autonomous navigation in agriculture is highlighted in [3], focusing on the importance of effective implementation of artificial intelligence, development of accurate and affordable sensors, and collaboration between agricultural machinery and agronomy to advance this sector.

A robust approach is presented in [4], where an apple harvesting robot with multiple arms is developed, facing labour reduction. A recognition and localization algorithm based on stereo vision and deep learning is proposed, with results in localization error reduction and improvements in harvesting efficiency. The creation of an autonomous localization and navigation system for agricultural robots is described in [5], with emphasis on creating and updating maps and localization accuracy in greenhouses, facilitating autonomous routes and meeting the required specifications. The challenge of accurate agricultural crop sensing is addressed in [6], employing Rand Augment (RA) to improve sensing performance through geometric and photometric transformations. The YOLOv3 model with transformations achieves significant improvements and is implemented in a robotic harvesting system. Rice seedling detection and classification by UAV is explored in [7], using a deep learning approach with adaptive filtering and recurrent neural network models, demonstrating improvements compared to other models. Apple detection in commercial orchards is addressed in [8] using two neural network models trained with deep learning. The SSD-Mobilenet and Faster R-CNN models achieve high accuracy rates, improving yield predictions for growers. For pitaya harvesting, [9] proposes an autonomous mobile robot system based on the Artificial Intelligence of Things (AIoT), combining 2D SLAM and AI object recognition for efficient navigation and harvesting. The accuracy of the recognition model reaches 96.7%. The Application of SLAM technology in agricultural environments is explored in [10], highlighting the theory, development and applications of this technology for map building and navigation of agricultural robots, as well as the challenges and future directions. The creation of the "Tomato Plant Factory Dataset" is presented in [11], benefiting automated sensing in control systems, robotic operation and performance estimation in plant factories.

A two-stage deep learning-based approach for apple detection and classification is described in [12], using YOLOv7 and EfficientNet-B0 models to improve the effectiveness of autonomous harvesting and avoid damage. The efficiency and functionality of agricultural crop harvesting are addressed in [13] by kinematic and dynamic analysis of hybrid robots combining open and closed-loop manipulators. The use of 2D LIDAR SLAM in mobile agricultural robots is proposed in [14] as a positioning scheme in hidden environments, achieving autonomous navigation accuracy in static environments. Automation of traditional Japanese orchards is explored in [15] using a LIDAR-based spraying system and machine learning algorithms, demonstrating the ability to compute real-time routes and operate safely in pesticide spraying tasks. Taken together, these works represent significant advances in automated fruit harvesting and autonomous navigation in agriculture, addressing fundamental challenges and presenting innovative solutions to improve efficiency and accuracy in these processes.

3. Methodology

This article presents the development of a drone system for crop monitoring during the harvesting stage in the Majes valley, Arequipa. In order to control this system, it has been developed as follows, see Figure 1.

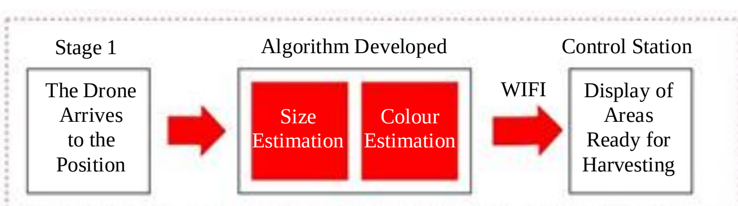

Fig. 1 Block diagram of the proposed system

First, the drone is trained so that it can perform the route to be monitored automatically and autonomously; for this, it sets the route of the trees to be surveyed. This drone has a camera to obtain the images in real-time, and through an algorithm developed, the colour and size of the target, which is the avocado fruit, can be accepted. After finishing the task via WiFi communication, the data obtained is processed, and the areas where the fruits are ripe for harvesting are determined based on size and colour.

4. System Development

4.1. Drone Stage

In this stage, the route that the drone will have to follow during its patrol in the neighbourhoods was established. The route was determined based on the distribution of the trees where the tests were conducted. The research was conducted with a Xiaomi FIMI X8 SE drone, which is a foldable aerodynamic drone equipped with intelligent control and wireless communication.

In addition to having a camera capable of recording 4K video at 30fps and transmitting HD images in real-time. In order to establish the trajectory to be followed, the 'Waypoints' function is used, where the different points of the route are established, along with the time that will be maintained in some positions, the flight speed, and the configuration of the height of elevation of the drone for the inspection of the fruit trees, as shown in Figure 2.

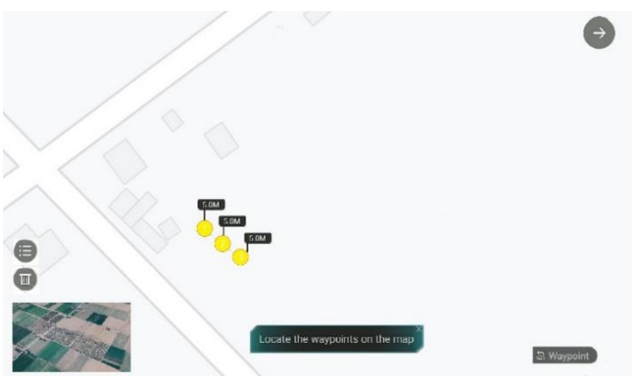

Fig. 2 Setting the drone flight

4.2. Algorithm Developed

To perform the avocado detection process, the collection of video and images is initiated using the cameras built into the drone. These real-time images aid in the identification and analysis of avocados concerning size and maturity.

The determination of size and maturity is accomplished through the Application of an algorithm developed in the Python language. Before processing the images provided by the drone, a pre-processing stage is undertaken, wherein the resolution is reduced from 3840x2160 (4k) to 858x480 (480p) to enhance processing speed.

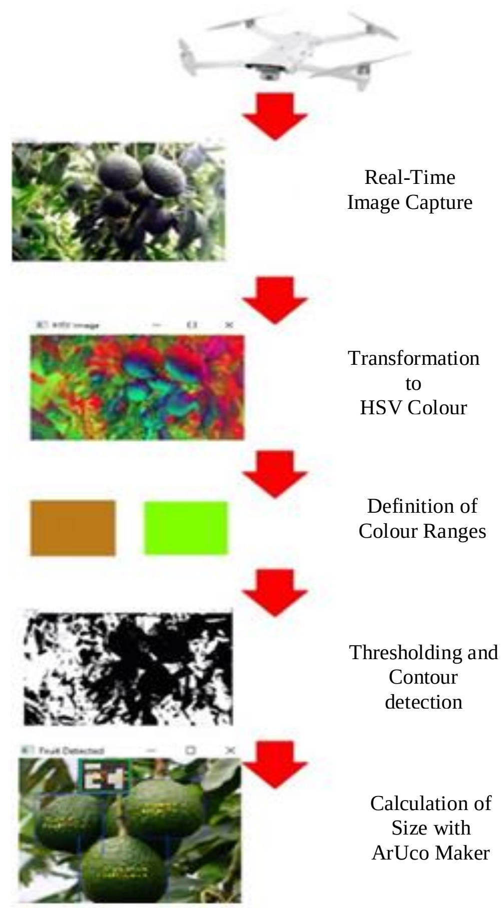

Fig. 3 Algorithm developed

To develop the image processing, two Foxeer Razer Mini cameras were utilized, with the objective of estimating the required measurements using triangulation methods, Camshift, and ArUco marker. The Kalman filter was employed to enhance the algorithm, and the procedure for analyzing the maturity of the fruit is detailed in Figure 3.

4.2.1. Sizing with Stereo Vision

The CAMSHIFT tracking method uses the position of the centroid and the zeroth order moment of the search window in the previous frame to determine both the location and dimensions of the search window in the next frame. (See Figure 4) [17]. Considering the computational load of a tracking algorithm and the distance evaluation, the centroid of the CAMSHIFT algorithm is used as the pixel position in both cameras to perform the triangulation.

Figure 5 shows the distance estimation based on stereo vision; CO_1 and CO_2 are the optical centres of each camera, f is the focal length of each lens, D is the distance between the centres of the cameras, and W is the distance between the object (in this case the fruits) and the stereo cameras. Both images obtained from the stereo camera are processed at the same time.

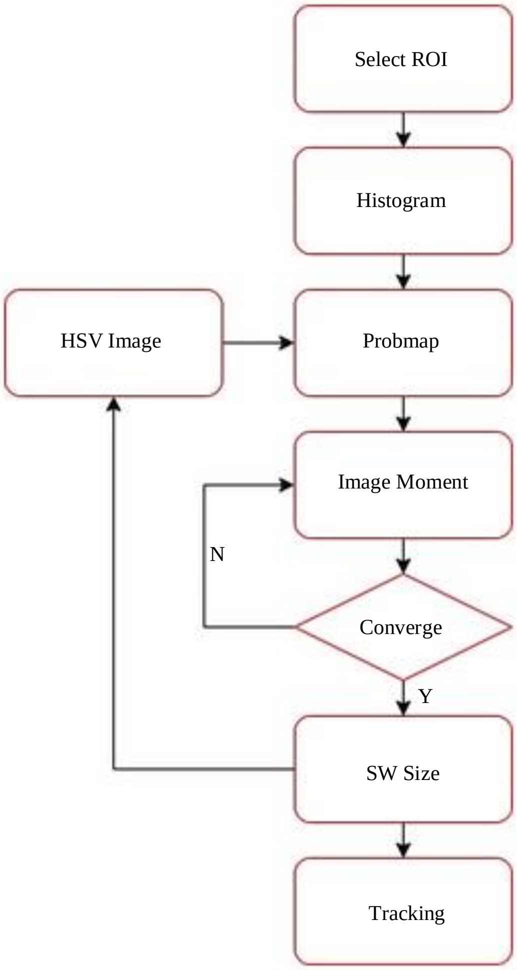

Fig. 4 Camshift

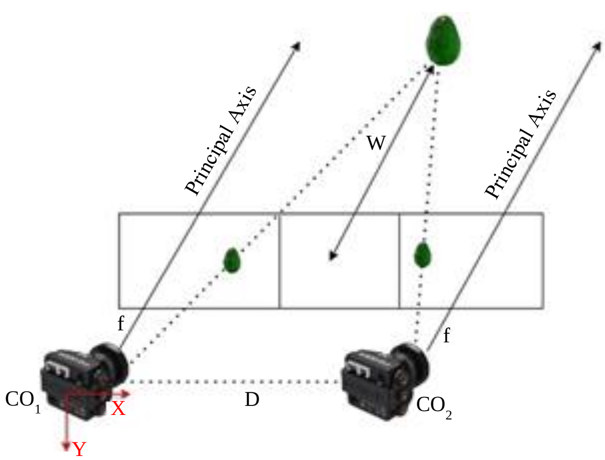

Fig. 5 Triangulation method for measurement estimation

The data obtained from the information about the analysis object in both pictures is used to calculate the size and estimate the distance. The disparity value, or X in pixels, between the analysis object in the two images is used to estimate the distance. The disparity is defined as the difference in pixels between the two center lines of the width of the analysis object as the camera is oriented parallel. The following formula can be used to determine the object distance or X:

$$X = ß\, x^{-1} \qquad \text{Where} \qquad ß = b\, f \tag{1}$$

It is determined that f is the focal length of the cameras, and b is the distance between the two cameras. The disparity value in pixels "x", the pixel value of the width "w", and the height "h" of the spot were used in the calculations for the size estimation, which is composed of the width and height. The ratio of the width per pixel (λw) to the height per pixel (λh) with the disparity is used to calculate the actual width (W) and height (H) of the analyzed object. Our investigation revealed that the values of the width per pixel and height per pixel of an object are linear and are inversely proportional to the disparity. With the following equation, we can calculate the width, W, and height, H:

$$W = \lambda_w w \qquad H = \lambda_h h \tag{2}$$

From a linear equation of a plot of λw and λh versus x, λw and λh are found as follows:

$$\lambda_w = m_w x + c_w \qquad \lambda_h = m_h x + c_h \tag{3}$$

Where c is the value of λ at x = 0 and m is the slope of the graph. Plotting the graphs of λw and λh versus x involves performing experiments with multiple samples whose width and height are known in reality. A different disparity value can be obtained by changing the distance from the object to the camera.

4.2.2. Sizing with ArUco Marker

To calculate the size of the avocados and to classify them as ripe or unripe, the ArUco library was used, which uses square markers for the estimation of the camera pose, reference point or measuring point. A 5x5 ARC measuring 4 cm on each side is used (see Figure 6). First, detect and find its perimeter (16 cm). Then, a simple rule of three is performed to determine how many pixels each centimetre is equivalent to. Once obtained, the equivalence in centimeters is all the lengths in pixels that can be divided by this value to get the measurement in centimeters.

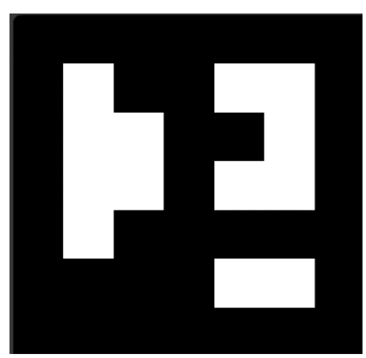

Fig. 6 ArUco is used as a reference point

This marker is placed on each avocado tree so that when the drone passes, it stops to make the calculations. Manual measurements are made with a ruler to compare them with the measurements provided by the program to validate the accuracy of the code. (See Figure 7)

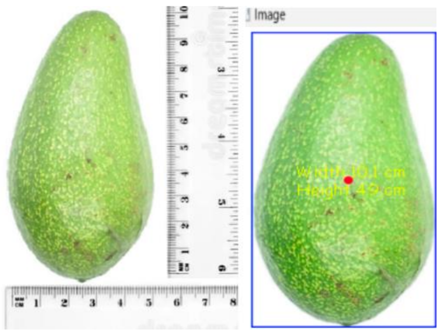

Fig. 7 Comparison of avocado measurements obtained manually vs Values obtained with ArUco marker

4.2.3. Calculation of Fruit Ripening Stage

Definition of Colour Ranges

When working in the HSV space, ranges of colours that correspond to ripe avocados are defined. These ranges are established by manipulating the hue, saturation and value values in the developed algorithm. These values were described as a maximum range and a minimum range; in the first one, the hue is close to an orange colour, and the second one is a totally light green.

Color Thresholding and Contour Detection

Using the cv2.in Range () function, a binary mask is generated to highlight pixels that fall within the defined colour range. This mask effectively separates the ripe avocados from the background and other unwanted elements, such as branches or leaves. The contours in the obtained mask are then identified. Using the function cv2.findContours(), the boundaries of the objects present in the image that match the colours defined for the ripe avocados are detected.

4.3. Control Station

A control station was developed that consists of a Raspberry Pi 4 8GB, which is responsible for processing the algorithm developed with the images provided by the drone, in addition, a second algorithm was developed, which is responsible for making a comparison between the values measured by our first algorithm with the standard average values of length and width of maturity of an avocado.

This algorithm is based on python code with conditional which values that meet or exceed these nominal data, the map will draw a green colour indicating to the user that in that area is ready for harvesting; otherwise it proceeds to display a reddish colour indicating that the fruit is not yet ripe for harvesting. (See Figures 8 and 9)

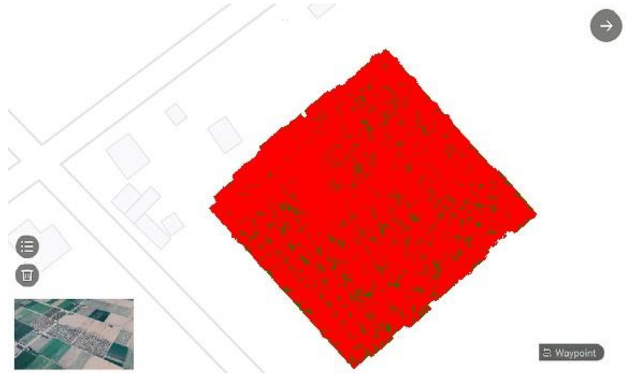

Fig. 8 Measurements estimated with the algorithm in the first stage

Figure 8 shows the data collected in the avocado ripening process; in this stage, most of the avocados are just beginning their development; therefore, our system shows the red colour as predominant.

On the contrary, Figure 9 shows the next stage of the crops, in which the green colour starts to be noticeable, which indicates that according to the comparison of our average values of the size of an avocado, there are units to proceed with the harvest stage, this is a good indication for our farmers since they can start with the harvest of the crops and thus avoid losses.

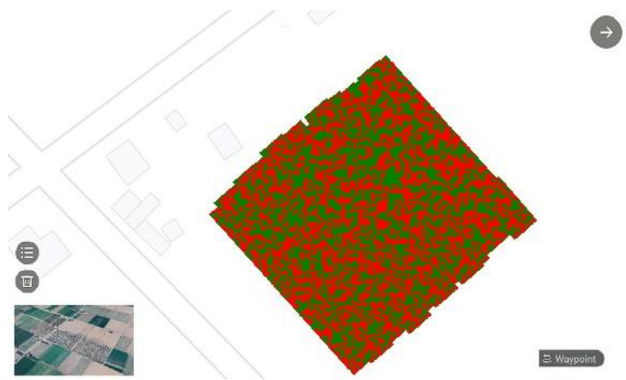

Fig. 9 Measurements estimated with the algorithm in the second stage

5. Test and Results

Both methods were tested, both for fruit size estimation with stereo vision (see Figure 10) and with ArUco Marker (see Figure 11). Twenty fruits were measured to determine which method had the best accuracy.

When analyzing the results of the comparison of the width and height measurements (See Figure 12), It was found that the ARC Marker method is more accurate than the stereo vision method. Therefore, the ArUco Marker method is used to test the complete system.

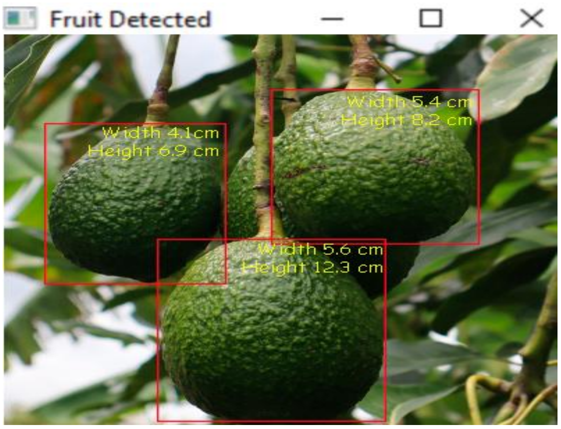

Fig. 10 Measurements estimated with the algorithm stereo vision

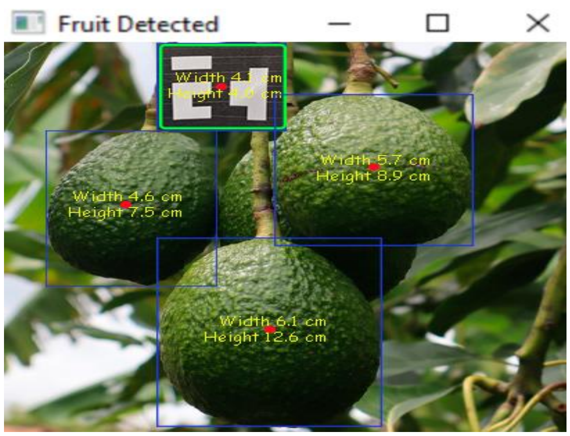

Fig. 11 Measurements estimated with the algorithm ArUco Marker

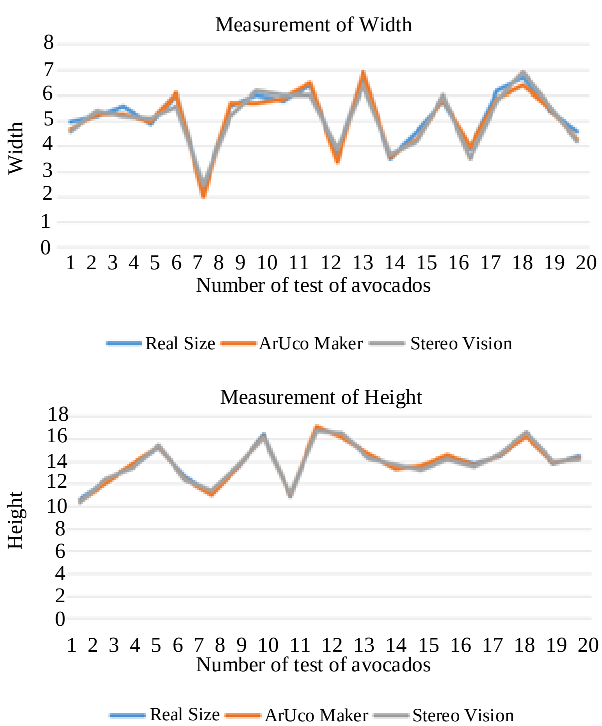

Fig. 12 Comparison of estimated measurements with real measurements

In order to validate the proposed system, 500 samples of avocado height and width measurements were tested. In this case, the error in measurements was considered, i.e., the human error when taking the samples; Figure 13 and Figure 14 show the comparative values we measured manually with the measurements obtained by our developed system.

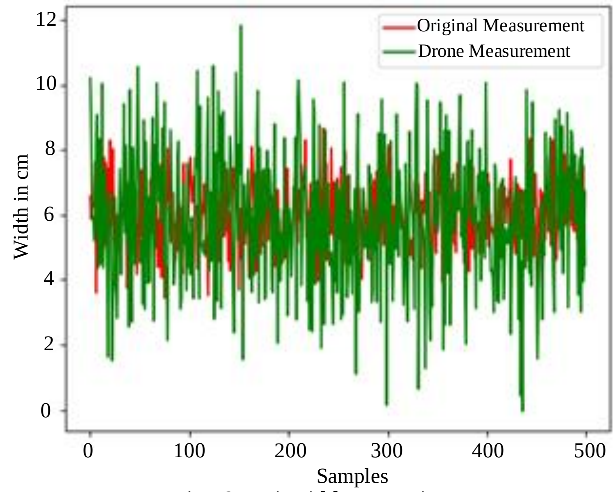

Fig. 13 Fruit width comparison

The main objective was to demonstrate the efficiency and accuracy of the algorithm in the identification of ripe and unripe avocados, as well as in the determination of avocado size. The results showed a detection rate of 93.5% for ripe and unripe avocados, with a false positive rate of less than 5%.

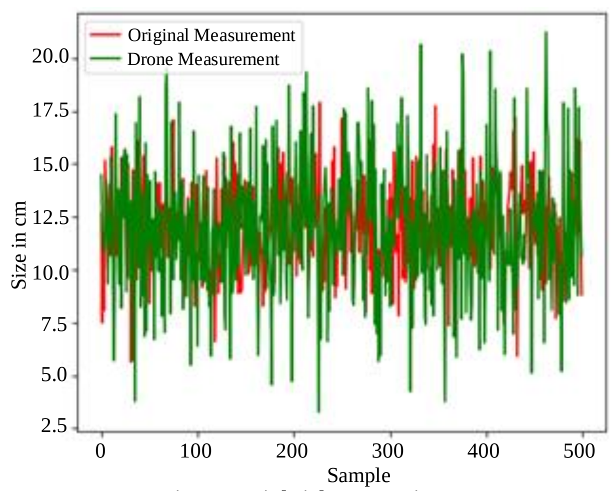

Fig. 14 Fruit height comparison

According to the data obtained, when comparing the accuracy of the developed algorithms, a 96% accuracy was achieved. This value is considered relevant and feasible to continue with the research. In addition, stable communication was established between the control station and the drone to obtain and process images in real-time, with no loss of information.

6. Conclusion

This paper focuses on the monitoring and evaluation of avocado maturity during the harvest stage using advanced computer vision technologies and drones. The results obtained demonstrate the feasibility and effectiveness of the proposed system, both in the detection of avocados with 93.5% and in the estimation of their measurements with 96%.

The generation of a map based on the collected data provided a more intuitive visual representation of the spatial distribution of avocados at different stages of maturity for users. This tool could prove invaluable to growers in making informed decisions about harvesting and management of their orchards. All the developments that have been obtained inspire future work, which will consist of adapting a robotic arm for the automatic harvesting of ripe fruits. The user interface will be improved to be more intuitive and accurate in displaying data to the user.

Acknowledgments

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