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Intelligent Robots for Fruit Harvesting: Perspectives on Their Implementation in Central America

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***Abstract*—Central American agriculture plays a fundamental role in the region's economy, ensuring food security and providing employment for much of the population. However, it faces critical challenges including outdated agricultural practices, limited technological access, and increasing climate vulnerability. Current reliance on traditional methods has led to reduced productivity and increased exposure to adverse climatic conditions.**

This work aims to evaluate the potential of intelligent robots for fruit harvesting as a transformative solution to modernize agriculture in Central America.

A review was conducted of state-of-the-art robotics in agriculture, focusing on intelligent systems that incorporate artificial intelligence, computer vision, and advanced sensors. The study included both global references and Central American case studies, such as apple and strawberry harvesting robots, as well as local innovations like UAV seed planters and coffee harvesters.

While advanced harvesting robots show promising results in fruit detection and handling through 2D/3D vision and soft actuators, implementation in Central America remains limited. The region focuses more on monitoring than autonomous harvesting, although pilot projects exist.

Main challenges include high costs, lack of technical infrastructure, and limited training. Nonetheless, intelligent robots could reduce labor dependency, increase precision, and improve resilience to climate extremes.

To facilitate broader adoption, future work should focus on low-cost development, local crop adaptation, training programs, and collaboration between governments, academia, and private sectors.

***Index Terms*—Smart agriculture, fruit harvesting, agricultural robotics, Central America, precision farming.**

I. Introduction

Central American agriculture has played a crucial role in the economy, providing employment and income to a significant portion of the population and contributing to food security both nationally and regionally. However, this sector faces multiple challenges that require attention and substantial improvements [1]. One of the main problems is the lack of modern technology and advanced farming practices, which limits the productivity and efficiency of the sector [2]. Many farmers still rely on traditional methods that do not leverage available technological advancements, resulting in low yields and greater vulnerability to adverse climatic conditions [3].

Moreover, agriculture in Central America faces the challenges of climate change, such as droughts, floods, and rising temperatures, which affect water availability and crop health. These extreme weather events threaten food security and the livelihoods of farmers, especially those who depend on subsistence agriculture [4].

In this context, the adoption of intelligent robots for fruit harvesting represents a transformative opportunity for agriculture in Central America. Intelligent robots, equipped with advanced technologies such as artificial intelligence (AI), computer vision, and sophisticated sensors [5], can identify, select, and harvest fruits with precision and efficiency. These technologies have the potential to modernize and optimize harvesting processes, increasing efficiency and crop quality, and providing more effective solutions to climate and food security challenges [6] [7].

Currently, various robots with different technological integrations are being developed, focusing on specific crops of interest. Among the crops used as a base are apples, for which 2D and 3D vision systems have been developed for detection and localization; for harvesting activities, actuators such as grippers that rotate or pull the fruit have been used. Another example is strawberries, which, due to their delicate nature and growth pattern, require a precise vision system and an extremely soft end effector [8].

On the other hand, Central America has not widely developed harvesting activities using robots, focusing more on monitoring or control tasks. There is the case of a seed-planting robot operated via UAV, designed to perform this activity systematically [9]. Additionally, there are other examples that directly address the topic, such as the development of a coffee harvesting robot at a university in Honduras [10].

This article aims to examine fruit harvesting robots in Central America, providing a comprehensive overview of how these emerging technologies are being integrated into the region's agriculture. Through a detailed analysis of technological advances and current research, this study seeks to identify key areas for future exploration and highlight opportunities to modernize and revitalize the agricultural sector in Central America. The article is structured as follows: first, the introduction presents the study's context and objectives. Next, the landscape of existing technologies related to intelligent fruit harvesting robots is explored. Then, the research methodology is described. Subsequently, the results are presented and analyzed in relation to the established theoretical framework.

Finally, the key findings are summarized in the conclusions, emphasizing the need to increase the application and investigation of intelligent fruit harvesting robots in Central America.

II. Intelligent Robots for Fruit Harvesting

The definition of a robot within the context of precision agriculture refers to an autonomous or semi-autonomous instrument capable of moving through crops, perceiving its environment, collecting relevant phenotypic information, and performing specific tasks through the integration of various technologies such as artificial intelligence, computer vision, and advanced sensors [11]. According to Wang et al. [11], these systems are usually composed of perception, control, and mobility modules, allowing them to operate effectively in various agricultural scenarios, whether open fields or greenhouses.

The functional classification of agricultural robots can be organized into three main categories: harvesting robots, oriented toward selective or mass fruit and vegetable harvesting; monitoring robots, which inspect crops using RGB cameras, multispectral sensors, or LiDAR technology; and assistance robots, which support tasks such as precision seeding, fertilizer application, or phytosanitary product delivery. Additionally, the emergence of hybrid systems capable of combining multiple tasks on a single robotic platform is noteworthy [12].

According to Wang et al. [13], this classification can be further deepened based on usage scenarios (open fields, greenhouses) and mobility structures, distinguishing between self-propelled platforms, track-based movement systems, and compact robots with robotic arms for high-precision operations. The implementation of these systems has transformed traditionally manual agricultural processes by increasing operational efficiency, reducing labor dependence, and improving precision in crop management. Their adoption has been more pronounced in countries with highly technologized agriculture, especially for harvesting fruits such as apples, strawberries, grapes, tomatoes, and citrus.

The visual perception module is the critical interface between the robotic system and its environment, whose main function is the precise detection and localization of fruits to enable autonomous harvesting [12]. This module captures and analyzes images using 2D or 3D sensors to identify fruits based on color, shape, and texture characteristics. RGB cameras employ machine or deep learning techniques based on visual properties, though they face limitations under variable lighting conditions or when the fruit color is similar to the background [14].

Alternatively, spectral sensors provide greater discrimination through the analysis of different wavelengths, although they are expensive and require intensive computational processing. There are also thermal sensors, useful for distinguishing fruits based on temperature differences, although their effectiveness decreases in shaded environments [14].

Regarding spatial localization, stereoscopic cameras, LiDAR sensors, and RGB-D cameras allow for the acquisition of three-dimensional coordinates. RGB-D cameras, for example, combine image and depth information in real time and are more economical and accurate than LiDAR sensors, although less effective under strong sunlight or at short distances [15].

These technologies enable the development of intelligent robots capable of identifying and harvesting fruits accurately and efficiently, reducing damage to the product. Although still in the research phase, these platforms continue to evolve with improvements in sensors and algorithms.

They also offer the possibility of building intelligent robots capable of harvesting target fruits and monitoring plantations remotely, as observed in Fig.1. However, it is important to highlight that these systems are still under development, leading to studies of different robots with varied methods or sensors. Each of these robots achieves high success margins and aims to keep fruit damage to a minimum, depending on the type of fruit being handled.

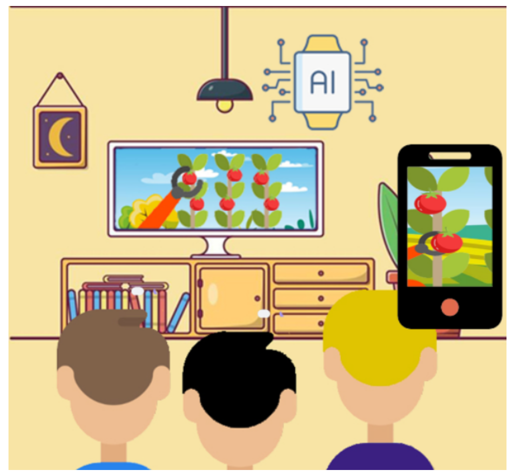

Fig. 1. Crop observation from home

III. Major Crops in Central America and Their Harvesting Techniques

There are two main harvesting approaches implemented by farmers to reduce labor costs in orchards: selective harvesting and bulk harvesting.

Selective harvesting involves the use of robotic systems equipped with manipulators and end-effectors to grasp individual ripe fruits. These systems are typically mounted on mobile platforms and include computer vision to identify and selectively collect ripe fruits, as shown in Fig. 2A. Additionally, these robotic systems are believed to combine the efficiency of machines with the selective precision traditionally achieved by human labor. This form of harvesting has gained significant attention in both academic research and industry, emerging as the preferred method among fruit producers. The continuous and rapid development of AI and robotic technologies is paving the way for broader adoption of selective robotic harvesting in commercial environments [12].

On the other hand, bulk harvesting relies on applying vibration to fruit trees to detach the fruits, as illustrated in Fig. 2B. This method has been adopted by growers of various fruits such as apples, oranges, and cherries. Although bulk harvesting systems offer high efficiency, they present important disadvantages. Producers have expressed concerns about excessive damage that these machines can cause to both trees and fruits. Damage to the fruits directly affects their market acceptance, which is why research to minimize these negative effects remains an active area of study. Furthermore, the quality of harvested fruits may vary considerably, as it is common to collect underripe along with overripe fruits [16]. Properly coordinating ripeness levels throughout the orchard under a bulk harvesting system poses a significant challenge, directly influencing the optimal timing of harvest to reduce losses [8].

The data collected on the main fruit crops, agricultural mechanization levels, and harvesting techniques used in different Central American countries are presented in Table I, providing a comparative overview useful for evaluating opportunities for the integration of robotic technologies.

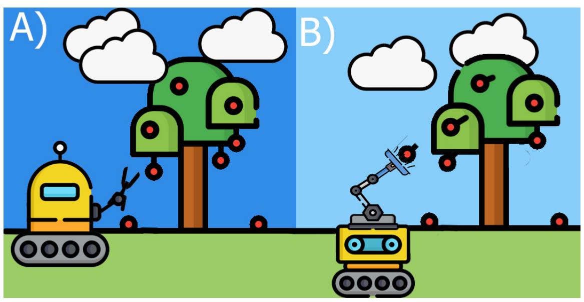

Fig. 2. Harvesting methods A) Force-based harvesting B) Vibration-based harvesting

IV. Discussion

The adoption of intelligent robots for fruit harvesting in Central America holds great promise for improving agricultural productivity and sustainability. However, several challenges must be addressed to fully realize this potential. These include technological limitations, economic considerations, and the specific needs and conditions of agriculture in the region. In this regard, research efforts have emerged to reduce the economic cost of building robots, such as in the case of Guatemala [23].

It is also essential for these robotic systems to have a strong capacity to detect, identify, and harvest fruits accurately [24]. Therefore, various strategies have been explored to improve performance. As shown in Fig. 3, each country focuses on different crops. For example, in El Salvador, coffee is the main crop targeted for technological improvement [2] [25] [26]. However, El Salvador shows less variety in crop-focused research compared to countries like Costa Rica, Panama, and Honduras.

According to the information summarized in Table I, Nicaragua shows increasing use of traditional machinery like tractors and seeders on small farms, but there is no evidence of robot implementation. Panama has low overall machinery availability, with mechanization emerging mainly in rice and

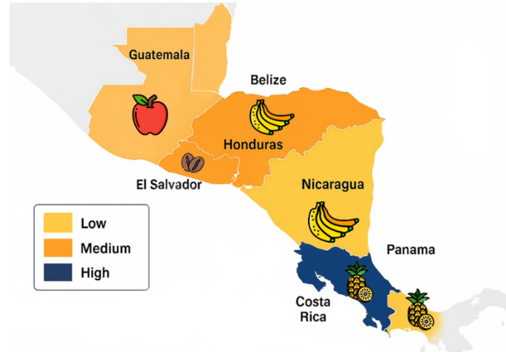

Fig. 3. Approximate levels of agricultural mechanization in Central America

corn cultivation using information and communication technologies. In Guatemala, agriculture remains small-scale and largely manual, although efforts have been made to develop low-cost UAV-based technologies.

Costa Rica stands out for incorporating LiDAR and remote sensors in sugarcane production, showing signs of emerging precision agriculture, although no robot-based harvesting techniques are reported. Honduras continues to rely heavily on manual labor, particularly in banana production, though pilot projects such as a coffee harvesting robot reflect initial advancements in automation. In El Salvador, moderate levels of mechanization are observed, supported by agricultural credit and the use of remote sensing; however, no robotic harvesting technologies are documented.

Belize lacks recent public or academic data, making it difficult to assess its status regarding mechanization or robotics in agriculture.

Current sensor and vision systems, including 2D and 3D cameras, have their respective strengths and limitations. For instance, 2D cameras are affordable and accessible but struggle under variable lighting conditions. On the other hand, 3D sensors such as LiDAR and RGB-D cameras offer better spatial precision but are often costly and face operational challenges in the harsh environmental conditions typical of the Central American climate [15].

Integrating machine learning algorithms with sensor data is critical to enhance the accuracy and efficiency of robotic harvesters. However, these algorithms require large training datasets and significant computational resources [27]. These computational demands, along with the need for real-time processing capabilities, pose considerable challenges, particularly in rural areas with limited access to high-performance computing infrastructure [12].

The initial investment for adopting robotic technology may be prohibitive for many small-scale farmers in Central America. Costs associated with the purchase, maintenance, and upgrading of robotic systems and advanced sensors must be considered and weighed against the potential long-term benefits of increased productivity and reduced labor costs.

Moreover, introducing advanced technologies into agriculture requires specialized training for farmers and operators.

TABLE I

SUMMARY OF FRUIT CROPS, MECHANIZATION, AND HARVESTING TECHNIQUES IN CENTRAL AMERICAN COUNTRIES.

Ref	Country	Main Fruit Crops	Mechanization	Harvesting Techniques
[17]	Nicaragua	Banana, plantain, coffee	Increased use of traditional machinery on small farms (tractors, seeders, etc.)	Use of harvesters and threshers; no evidence of robots
[18]	Panama	Pineapple, plantain, citrus, coffee	Low machinery availability; mechanized rice and corn; emerging ICT	Partial mechanization of rice and corn; ”chuzo”-type planting with technology
[19]	Guatemala	Pear, apple, plum, peach	Small-scale agriculture without advanced mechanization; manual handling	No specific techniques described; no mechanization or robotics
[20]	Costa Rica	Pineapple, banana, sugarcane	Use of remote sensors and LiDAR in sugarcane; emerging precision agriculture	Possible mechanization in sugarcane; no detailed techniques reported
[21]	Honduras	Banana (Gros Michel, Cavendish)	Railway infrastructure and agrochemical use; no mention of modern machinery	Intensive manual labor; machete use; mobile planting system
[22]	El Salvador	Coffee, sugarcane, corn, beans, sorghum	Moderate mechanization with credit support; use of remote sensors and remote sensing	No specific techniques detailed; no robotic implementation
-	Belize	–	No updated public or academic information found	–

This includes training in the use and maintenance of robotic systems as well as interpreting the data they generate. The lack of accessible and effective training programs can limit the adoption of these technologies.

Implementing intelligent robots has the potential to significantly enhance the efficiency of harvesting operations, reduce labor dependency, and improve the speed and precision of harvesting. This can result in higher production and better quality of agricultural products.

Intelligent robots can also help farmers adapt to adverse climate conditions through timely crop monitoring and harvesting. This can improve the resilience of agriculture in Central America against extreme climate events.

Finally, the adoption of robotic technology can drive innovation and development in the agricultural sector, attract investment, and promote research in advanced agricultural technologies. This could contribute to the modernization and revitalization of agriculture in the region. In conclusion, while the adoption of intelligent robots for fruit harvesting in Central America presents significant challenges, it also offers transformative opportunities to enhance the region's agricultural efficiency and sustainability. Addressing these challenges will require a combination of technological advancement, economic investment, and effective training programs.

V. CONCLUSION

The adoption of intelligent robots for fruit harvesting represents a transformative opportunity to modernize agriculture in Central America, despite existing technological and economic challenges. If properly addressed, these advanced technologies could significantly boost the region's efficiency, sustainability, and food security.

The integration of artificial intelligence, computer vision, and robotics in fruit harvesting can reduce the reliance on manual labor, enhance crop precision, and mitigate the risks posed by climate change. Such innovations promise not only to streamline agricultural operations but also to increase crop quality and reduce post-harvest losses.

Nevertheless, successful implementation will depend on reducing costs, ensuring accessibility to small and medium-sized farmers, and providing training programs to operate and maintain robotic systems. Government and private sector collaboration will be essential to create incentives, infrastructure, and regulatory frameworks that support the adoption of these technologies.

In summary, intelligent robots can serve as a catalyst for agricultural innovation in Central America. Their development and deployment should be strategically supported to unlock their full potential and lead the region toward a more resilient and modern agricultural future.

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