https://doi.org/10.17163/abyaups.92.699

Development of an intelligent system for fruit detection and cutting using computer vision

Mayra Comina
Universidad de las Fuerzas Armadas-ESPE, (Ecuador)
Orcid: https://orcid.org/ 0000-0002-1541-4850

Alexandra Verdugo
Universidad de las Fuerzas Armadas-ESPE, (Ecuador)
Orcid: https://orcid.org/ 0000-0001-9328-0248

Jorge Comina
Universidad Politécnica Salesiana, (Ecuador)
Orcid: https://orcid.org/ 0009-0004-0402-2474

Walter Verdugo
Universidad Politécnica Salesiana, (Ecuador)
Orcid: https://orcid.org/ 0000-0002-0656-0135

Introduction

In the food industry, process automation is essential for improving efficiency, productivity, and ensuring product quality. Computer vision has emerged as a powerful tool for the automated detection, classification, and manipulation of fruits and other foods (Fan et al., 2024). This technology enables precise and rapid identification of characteristics such as type, ripeness, and quality, facilitating processes like classification, packaging, and quality control (Patil et al., 2023).

Computer vision utilizes artificial intelligence and machine learning algorithms to analyze images and extract relevant information, allowing high-precision classification of fruits based on shape, color, and texture (Del Castillo et al., 2021). Recent studies have highlighted the potential of this technology to enhance efficiency and quality in food production, such as defect detection in fruits and vegetables, grain and seed classification, and fish species identification (Kang & Chen, 2020).

The relevance of computer vision and artificial intelligence algorithms for object detection has expanded across various fields, including industrial processes, quality control, and automation, proving indispensable in Industry 4.0. Applications extend beyond industry to scientific and security sectors, significantly improving processes in various companies (Sucari et al., 2020).

Research has demonstrated substantial improvements in process quality through the implementation of computer vision systems. These include systems for recognizing Latin American tropical fruits, using advanced techniques to enhance precision and efficiency in object identification and classification (Fan et al., 2020). The integration of artificial intelligence with computer vision has further advanced industrial quality control, employing deep learning techniques for high-precision fruit detection and classification (Javaid et al., 2022).

In smart agriculture, computer vision systems have optimized crop management, resource use, and yields (Sharma et al., 2022). Additionally, autonomous systems for fruit harvesting have shown remarkable advancements (Zhou et al., 2021). Computer vision techniques for inspecting agricultural product quality are replacing manual inspections, reducing errors, and improving economic efficiency (Da Costa et al., 2020).

This project aims to identify the technical characteristics of a computer vision system for real-time image acquisition and electronic component evaluation, focusing on five types of fruits: watermelon, apple, pear, orange, and banana. The development will follow the Quality Function Deployment (QFD) methodology to prioritize technical characteristics and include designing printed circuits and arranging elements in the graphical interface (Ruiz García, 2020). Tests will be conducted to validate the system's accuracy and improve detection algorithms (Amaral et al., 2023).

The rest of this article is organized as follows. In Section 2, the Methods are described. In Section 3, the results and the limitations as well as the contributions of this investigation are analyzed. Finally, the conclusions are presented in Section 4.

Materials and Methods

Module Identification

To identify the design modules, the QFD (Quality Function Deployment) matrix was used, which determines the most important technical characteristics of the project. Then, design modules were used for the selection of elements.

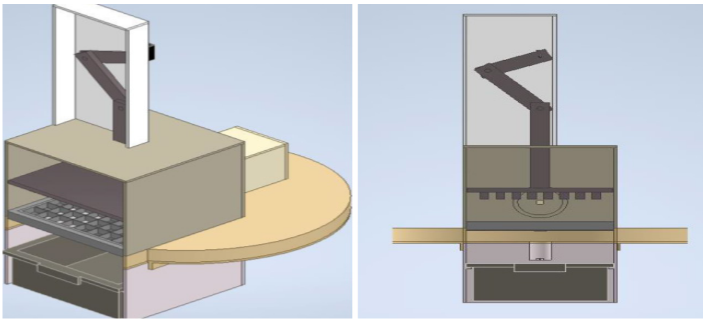
Table 1
List of elements

Design Module	Element
Detection Camera	ESP32CAM
Type of motors for blade movement	DC Motor
Type of mechanism for fruit cutting	Servomotor
Graphical interface for data visualization Matlab	Matlab
Control Board	Arduino UNO

System Design

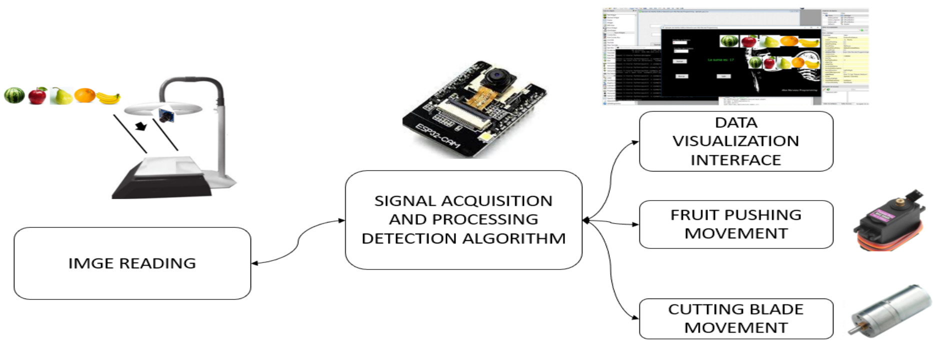
The system design was carried out using 3D modeling software and electronic simulation tools to ensure the correct integration of all components. Figure 1 shows the 3D design of the complete system.

Figure 1
3D Design of the fruit detection and cutting system



The Figure 2 shows the schematic diagram of the cutter.

Figure 2
Schematic Diagram



Detection Algorithm Programming

The detection algorithm was implemented using Python and programmed in the Matlab graphical interface. The flowchart of the detection algorithm is shown in Figures 3 and 4.

Figure 3
Flowchart of the detection algorithm

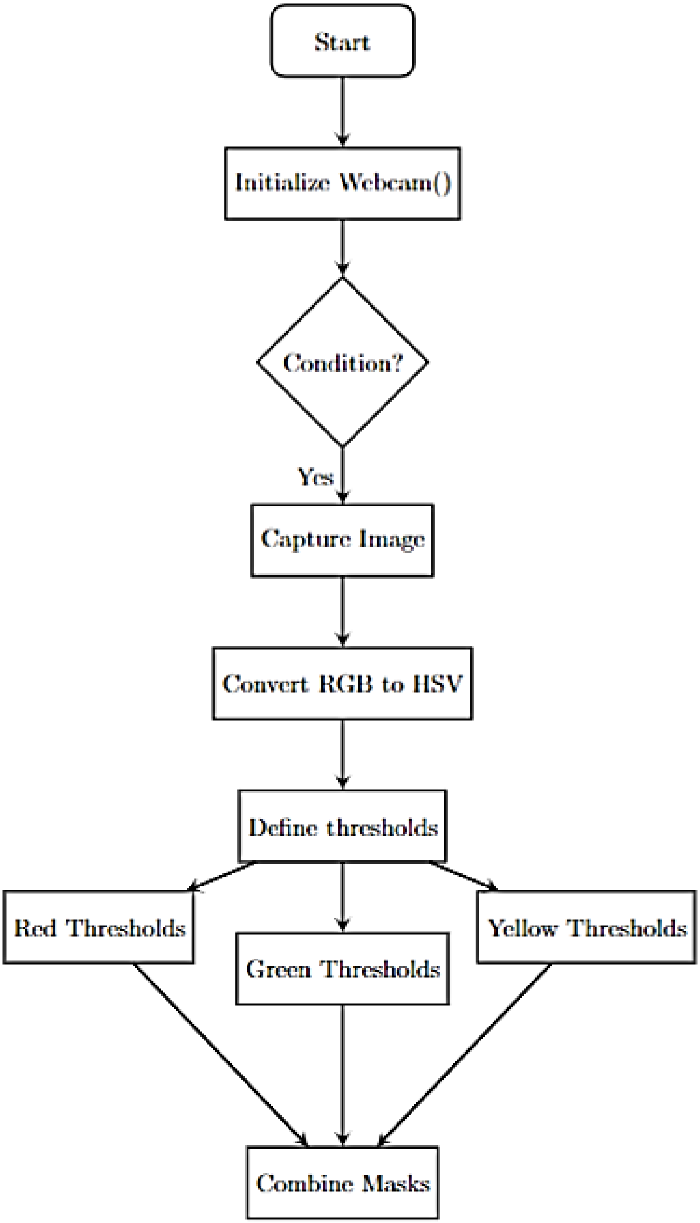
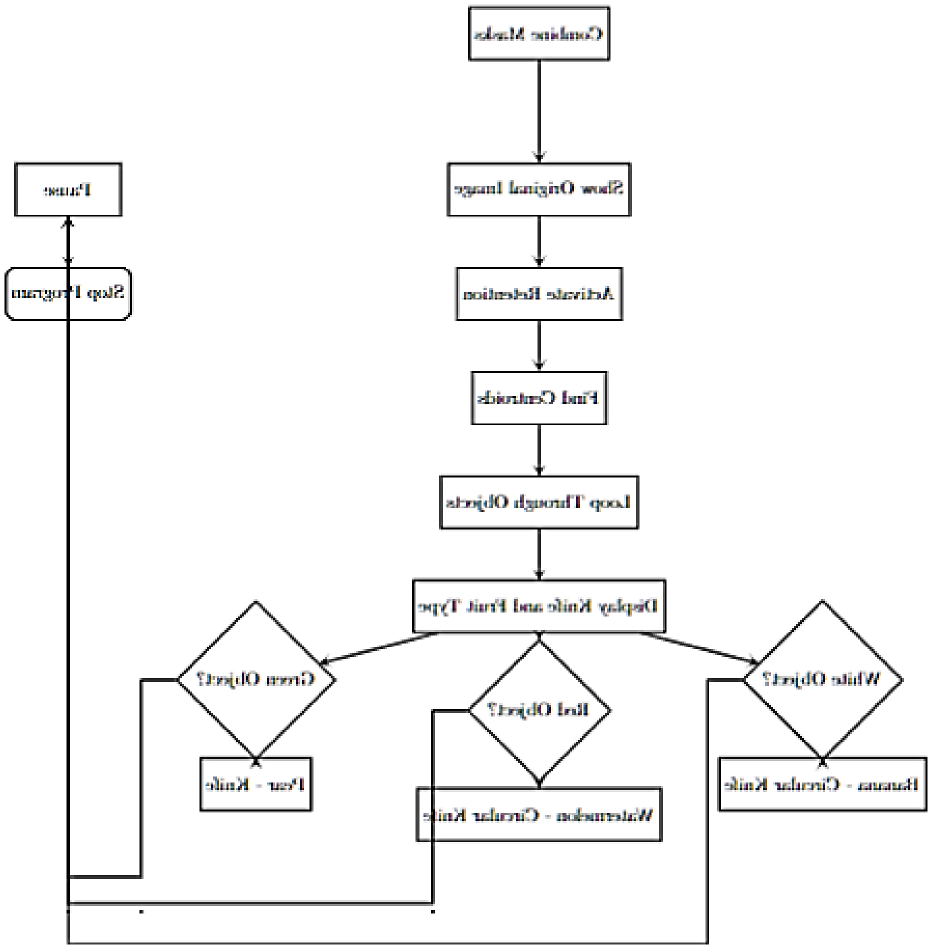


Figure 4
Flowchart of the detection algorithm



Results

This section presents the results obtained during the development and implementation of the fruit detection system. The tests conducted to verify the system's functionality and the analysis of the obtained results are described.

Development of the Hardware Construction Process

The construction process of the detection system was carried out by printing parts using a 3D printer. Figure 5 shows the assembly of the machine.

Figure 5
Machine assembly

Functionality Tests

Several tests were conducted to verify the functionality of the detection system. The tests included image acquisition, communication with the graphical interface, fruit detection, and the operation of the cutting mechanism.

Fruit Detection Test For fruit detection, the conditions of fruit type and blade assignment shown in Table 2 were considered.

Table 2
Conditions for Detection

Fruit	No. Color	Fruit Type	Assigned Blade
1	Intense Red	Watermelon	Grid - Circular
2	Green	Pear	Grid
3	Yellow-White	Banana	Grid - Circular
4	Yellowish Red	Apple	Grid
5	Orange	Papaya	Grid - Circular

Several fruit detection tests were conducted with different image acquisition backgrounds. Figure 6 shows the detection of the fruits.

Cutting Mechanism Functionality Tests of the downward movement of the axis mechanism and the cutting of the fruit were performed, as shown in Figure 7.

Figure 6
Fruit detection

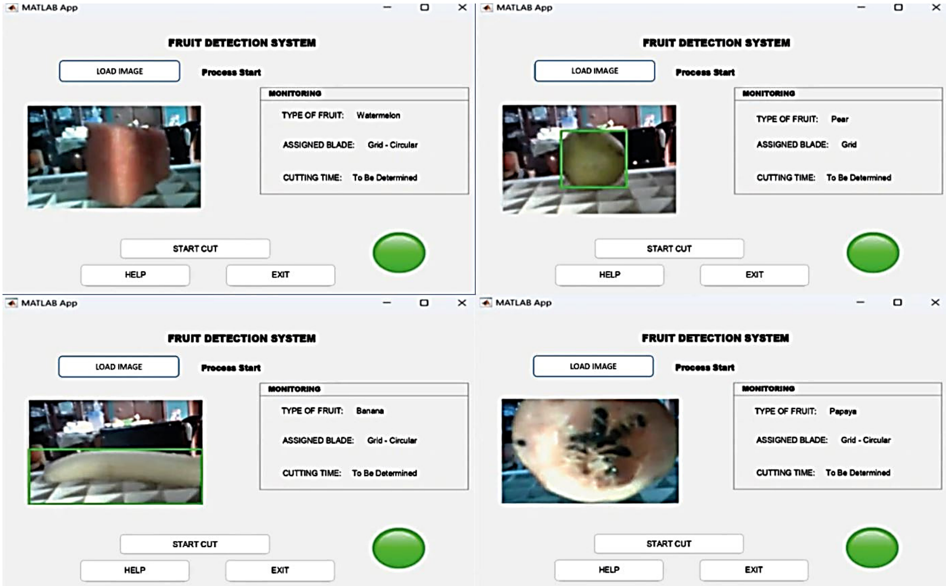
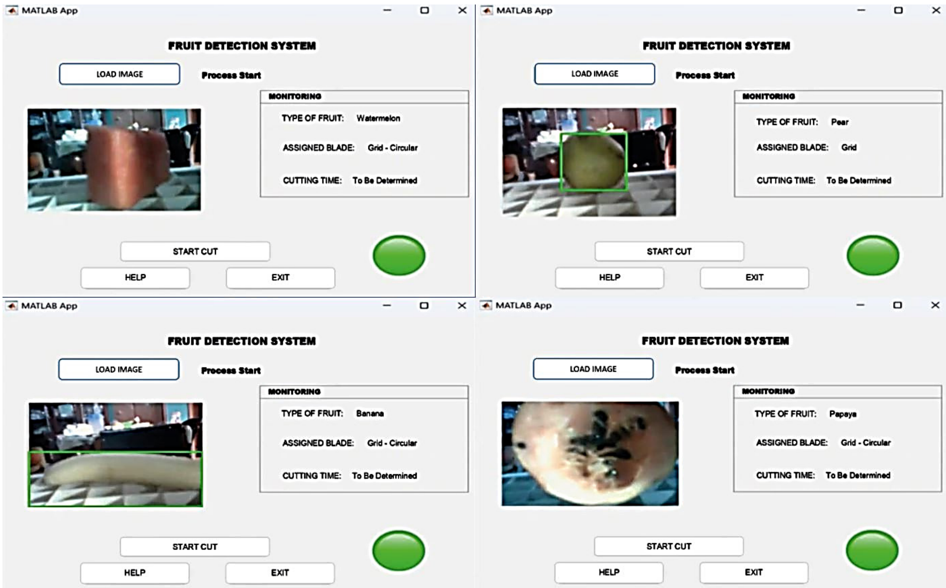


Figure. 7
Movement of the axis mechanism - downward

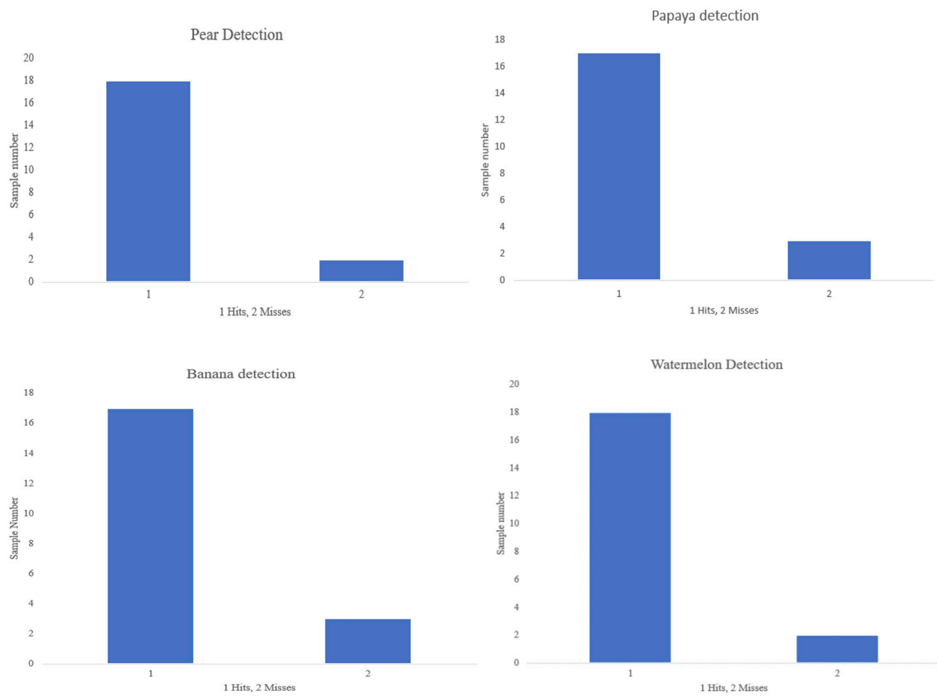


Analysis of the results

According to the main objective of this project, which is to detect five types of fruits using computer vision, the results obtained in the detection of each fruit are analyzed. Figure 8 shows the data of hits and misses in a set of 20 tests conducted for pear detection. It is observed that there are 18 hits and 2 misses in the case of pear detection.

Figure 8

Results of hits and misses for pear detection



Similar tests were conducted for the detection of other types of fruits, obtaining the following results:

Banana: 17 hits and 3 misses
Papaya: 17 hits and 3 misses
Watermelon: 18 hits and 2 misses
Apple: 14 hits and 5 misses

Conclusions

The fruit detection system using computer vision has proven to be an effective and precise solution for improving efficiency in fruit salad preparation in a domestic environment. During the tests, the following results were obtained: banana with 17 hits and 3 misses, papaya with 17 hits and 3 misses, watermelon with 18 hits and 2 misses, apple with 14 hits and 5 misses, and pear with 18 hits and 2 misses.

These results indicate a high accuracy in fruit detection, with an average success rate of 88.8% in the tests conducted. The system not only correctly identified the fruits but also selected the appropriate blade for cutting, optimizing the preparation process. This has significant practical implications, as an automated system like this can significantly reduce the time and effort required in food preparation, improving productivity and efficiency in domestic settings and potentially in small businesses.

Areas for improvement were identified in the detection of certain types of fruits, such as apples, where the success rate was lower. It is recommended to optimize the detection algorithm to improve precision and robustness under variable lighting conditions. Additionally, the use of advanced machine learning techniques could further enhance detection accuracy, and the integration of additional sensors could allow for better fruit classification.

The implementation of this system in other similar businesses could significantly improve their productivity and competitiveness. Future improvements could also include the development of industrial versions of the system in the food industry, where efficiency and precision in food preparation and processing are critical.

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