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Agricultural Mechatronics: Orange Sorting System Using Image Segmentation

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ABSTRACT

Sorting oranges after harvest is a critical step. It requires separating ripe fruit from unripe. Traditionally, this is done by hand. This method is inefficient and subjective. It is not suitable for modern agriculture. This study creates an automated system to solve this problem. The system uses mechatronics and image processing. Its core uses the HSV color space for image analysis. This method is effective for assessing the peel's color, which indicates maturity. The mechatronic system performs the physical sorting using a servo motor. It includes a conveyor belt, a digital camera, a processing unit, and an actuator. This research was tested on 30 sample oranges. The results show 90% accuracy in mechatronics sorting. This proves the system is a reliable and effective tool for quality control.

Keywords
Agricultural
HSV
Mechatronics
Orange
Sorting

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1. Introduction

Orange agriculture represents a cornerstone of the global agricultural economy [1]. This industry does not merely supply a beloved fruit; it underpins vast international supply chains for juice, concentrates, flavorings, and fresh produce, contributing significantly to both local and national economic frameworks [2]. However, the present-day landscape of orange cultivation is fraught with formidable and escalating challenges that threaten its sustainability and profitability. Unlike many grain or root crops, the harvesting of oranges remains an operation intensely dependent on human labor [3]. Each individual fruit must be carefully detached from the tree to avoid bruising, stem-puncture, and other damage that would accelerate decay and render it unmarketable. This necessity for manual dexterity and judgment has historically impeded full mechanization.

The act of harvesting is the first step in a longer journey to the consumer. A subsequent, and equally critical, stage is the sorting and classification of the fruit based on its maturity. The accurate division of ripe and unripe oranges is not a matter of convenience but a fundamental determinant of quality, market value, and consumer trust. A ripe orange possesses a specific chemical and sensory profile: a perfect balance of sugars and acids creating its signature sweet-tart flavor, a juicy and tender texture, and a vibrant, characteristic color that signals its readiness to eat [4][5]. This fruit meets consumer expectations and can be sold at a premium in fresh markets or be efficiently processed into high-quality juice. In contrast, an unripe orange is a commercial liability. Its flavor profile is dominated by acidic compounds, lacking the necessary sugars, resulting in a harsh and unpleasant taste. Therefore, the sorting process acts as the final quality control gate, the essential barrier that protects the integrity of the product and the financial investment of the grower. Traditionally, this task too has fallen to teams of workers on sorting lines, a method susceptible to human error, inconsistency, and the same labor shortages that plague the harvesting process.

Confronted by these persistent labor and quality control issues, the agricultural sector is undergoing a technological transformation, actively seeking automated solutions to enhance efficiency, reduce costs, and improve output consistency [6]-[8]. The implementation of technology, specifically automation, in orange sorting presents a compelling vision of the future. However, the path to realizing this vision is strewn with significant technical challenges. The primary obstacle is replicating, and ideally surpassing, the sophisticated perceptual and cognitive abilities of a human sorter. An automated system must be equipped with sensors capable of capturing these visual properties with high accuracy.

The technology integration is transforming orange agriculture. Key applications include robotics [9]-[11], image processing [12][13], Internet of Things (IoT) [14][15], and artificial intelligence [16]-[18]. These technologies are implemented through mechatronic systems that perform essential farming operations such as picking, sorting, transporting, and processing, thereby enhancing overall efficiency and productivity [19]-[22]. A highly promising architecture to solve is the integrated use of image processing technology within a robust mechatronic system schema. This approach breaks down the complex sorting task into a series of managed steps, each handled by a dedicated technological component working in harmony. The process begins with image acquisition. High-resolution digital cameras, strategically positioned above a conveyor belt, capture detailed color images of each orange as it is transported. Critical lighting systems, often using light-emitting diodes (LEDs) to provide consistent and uniform illumination without shadows, ensure that the images are clear and standardized, preventing variations in ambient light from affecting the analysis.

The paramount significance of this research lies in the practical development and validation of a fully functional prototype mechatronic conveyor system that seamlessly integrates real-time image processing to achieve accurate, automated sorting of oranges by ripeness. This research, therefore, is not an academic exercise but a crucial step towards building a more efficient, reliable, and profitable future for a critical global industry.

2. Method

The object of this research is the detection of orange peel color using HSV segmentation to determine its ripeness classification. The system designed for this device will detect the color from an image of the orange peel captured by a camera. This detection of the orange peel color employs the HSV segmentation method operated by a computer. Following identification, the oranges will proceed to an actuator in the form of a servo motor to be sorted according to their classification. The information presented, namely the count of ripe and unripe fruit, will be displayed on a 16x2 LCD.

2.1. HSV

The color segmentation process utilized the Hue, Saturation, and Value (HSV) color space to effectively isolate the skin color of the Siam oranges from the background. This color model was selected over the traditional RGB (Red, Green, Blue) model due to its superior performance in representing color in a way that aligns more closely with human perception, where color information (Hue) is decoupled from lighting intensity (Value). This characteristic makes it particularly robust against variations in illumination and shadows, which are common challenges in image-based fruit sorting. For this study, a specific range of Hue, Saturation, and Value thresholds were empirically defined to correspond to the distinct color profiles of ripe and unripe fruit, allowing the system to accurately pixelate and classify each orange based on the dominant color present in its peel.

2.2. Mechatronics System

This research implements an automated mechatronic sorting system. The system integrates machine vision, precision actuation, and mechanical conveyance. A regulated conveyor mechanism presents individual fruit to a digital imaging module. This module acquires a high-resolution image of each specimen. A computational unit processes the image utilizing the Hue, Saturation, Value (HSV) color model for segmentation. This analysis determines the maturity classification based on chromatic features of the peel. A command signal is subsequently dispatched to a rotary servo actuator. The actuator executes a predefined angular displacement corresponding to the maturity class. This action directs the specimen into its designated collection channel, thereby achieving automated sorting.

2.3. System Design

The system design is built around a centralized Arduino Uno microcontroller, which orchestrates all electronic peripherals. Electrical power for the entire system, including the conveyor drive, is supplied by an Accumulator (ACCU). A DC motor, governed by an L298N motor driver module under the Arduino's pulse-width modulation (PWM) control, provides the propulsion for the conveyor belt. An infrared (IR) sensor acts as the item detection module, signaling the microcontroller to initiate the sorting sequence upon an orange's arrival. The maturity classification is performed offboard; a digital camera captures an image of the fruit, which is then processed on a laptop using an HSV segmentation algorithm to determine ripeness. The classification result is communicated serially to the Arduino, which subsequently commands a servo motor to execute a precise angular movement, thereby pivoting the fruit into the appropriate collection pile. The wiring diagram can be seen on Fig. 1.

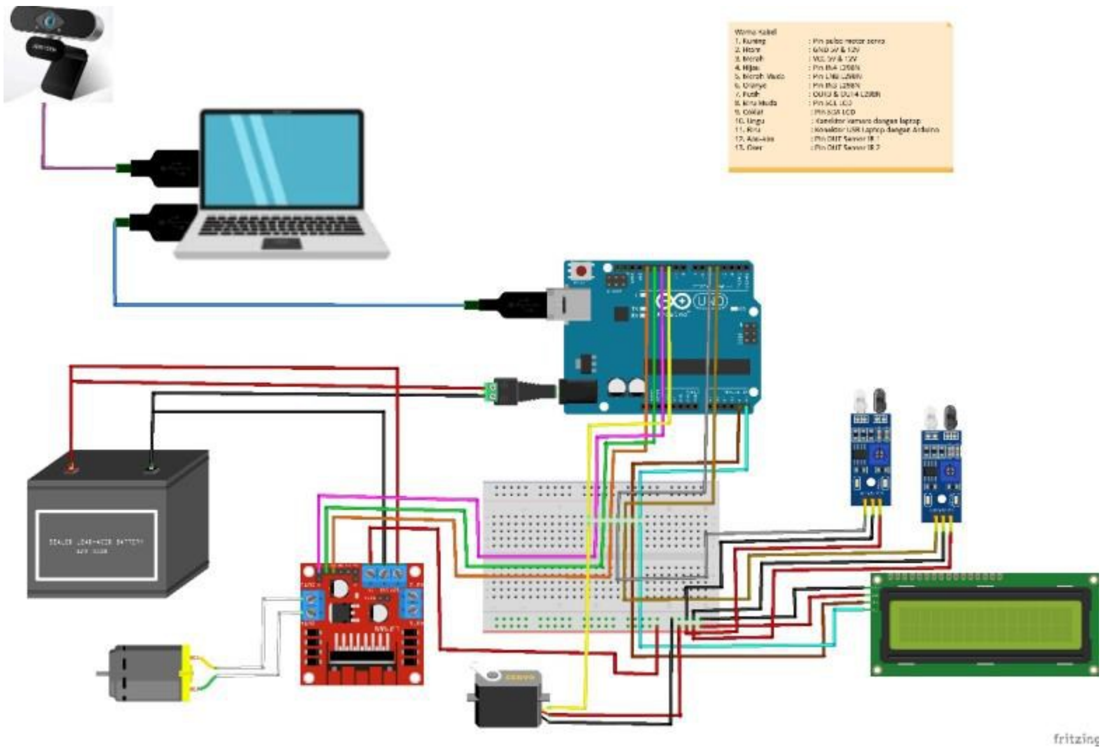


Fig. 1. Wiring Diagram

3. Results and Discussion

In this research, data acquisition for orange maturity sorting is conducted within the Visual Studio Code software environment. The system features a dedicated interface that displays the real-time identification process of orange maturity using a Python program. This interface presents two primary windows: one showing the original camera feed and another displaying the results of the HSV image thresholding process. The interface can be seen on Fig. 2. Furthermore, the real-time viewer provides quantitative data by calculating and presenting the average RGB and HSV values from a defined region of interest located at the center of the frame.

The data acquisition process will evaluate three distinct experimental scenarios to empirically determine the optimal Hue, Saturation, and Value (HSV) threshold range for accurately segmenting and classifying ripe oranges, with the objective of maximizing detection accuracy. These scenarios involve systematically modifying the HSV value intervals within the Python-based image processing program: Scenario 1 tests H: 10–20, S: 100–170, V: 100–170; Scenario 2 uses H: 30–40, S: 150–255, V: 150–255; and Scenario 3 employs H: 10–25, S: 100–255, V: 100–255. The derivation of these value ranges is grounded in prior research by Dwicahyo *et al* [23], which established reference RGB and HSV values for ripe oranges—specifically H: 4.62–10.59, S: 21.86–92.92, and V: 235.15–250.60—providing a scientific basis for the selected thresholds in this research.

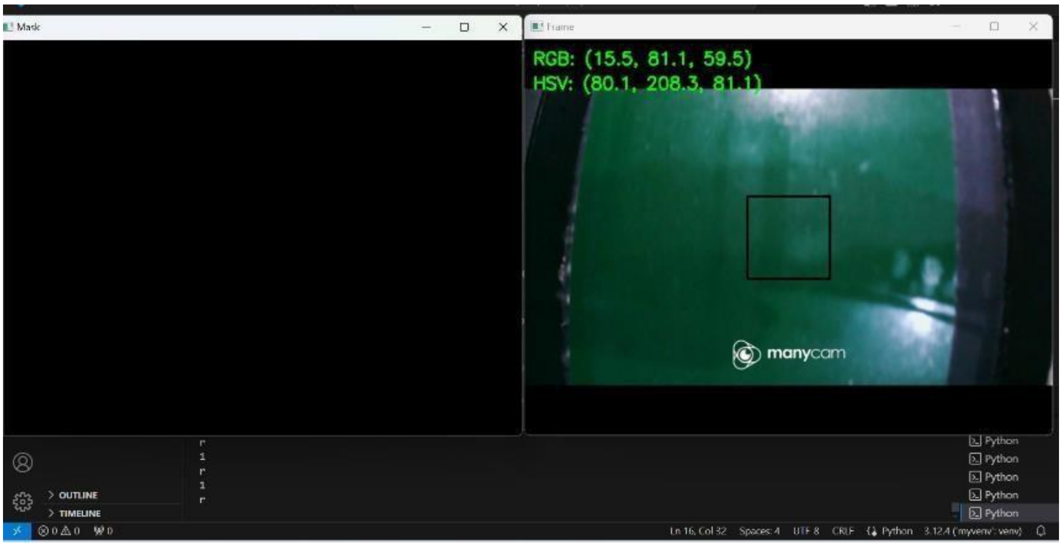


Fig. 2. Application Interface

3.1. Scenario 1

In the first scenario, the upper and lower threshold values for detecting ripe oranges were defined in the HSV color space as [20, 170, 170] and [10, 100, 100], respectively. The identification process was conducted using a dataset comprising 20 image samples ripe oranges and 10 image samples unripe oranges. Table 1 shows the detection of scenario 1 for ripe and unripe oranges.

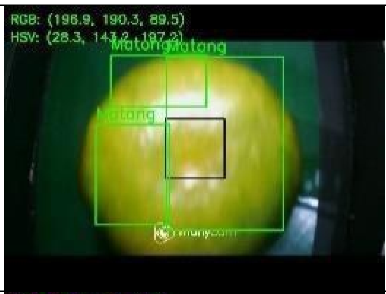
Table 1. Scenario 1

No	Visualization	Detection	Accuracy	Average
1		Ripe Detected : 19 Unripe Detected : 1	95%	92.5%
2		Ripe Detected : 10 Unripe Detected : 1	90%	

3.2. Scenario 2

For the evaluation of the second scenario, the HSV threshold range was reconfigured with an upper boundary set to [40, 255, 255] and a lower boundary set to [30, 150, 150] to assess its efficacy in detecting ripe Siam oranges. The experimental validation utilized an identical sample size for comparative purposes, consisting of 20 image samples of ripe oranges and 10 image samples from unripe oranges, thereby isolating the impact of the adjusted threshold values on classification accuracy. Table 2 shows the detection of scenario 2 for ripe and unripe oranges.

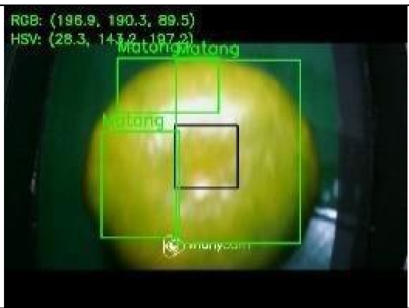
Table 2. Scenario 2

No	Visualization	Detection	Accuracy	Average
1		Ripe Detected : 15 Unripe Detected : 5	75%	87.5%
2		Ripe Detected : 0 Unripe Detected : 10	100%	

3.3. Scenario 3

In the third and final scenario, a distinct and broader HSV threshold spectrum was implemented to evaluate its performance in maturity classification, with the upper boundary set to [25, 255, 255] and the lower boundary defined as [10, 100, 100]. This configuration was tested under consistent experimental conditions, utilizing a standardized dataset of 20 image samples ripe oranges and 10 image samples unripe specimens to ensure comparative validity across all scenarios. The test result can be seen on Table 3. Based on the experimental results from scenarios one, two, and three, the HSV color segmentation-based system for orange maturity sorting demonstrated optimal performance and operated in full accordance with the initial design specifications. This was evident in both the precision of the HSV color identification process and the reliable mechanical function of the conveyor system, which executed its sorting tasks as intended.

Table 3. Scenario 3

No	Visualization	Detection	Accuracy	Average
1		Ripe Detected : 20 Unripe Detected : 0	100%	100%
2		Ripe Detected : 0 Unripe Detected : 10	100%	

3.4. Mechatronics System

Beyond evaluating the most effective HSV values for distinguishing orange maturity, this research also implemented these parameters directly within a functional mechatronic system. Fig. 3 show the complete sorting system using mechatronics method. This integrated system utilized a conveyor belt for fruit transportation and a servo mechanism for automated sorting. Across 20 trials conducted for each maturity category (ripe or unripe), the system achieved an overall accuracy rate of 90%. Some misclassifications occurred due to suboptimal lighting conditions and occasional slippage during the fruit transportation process can be seen in Table 4.

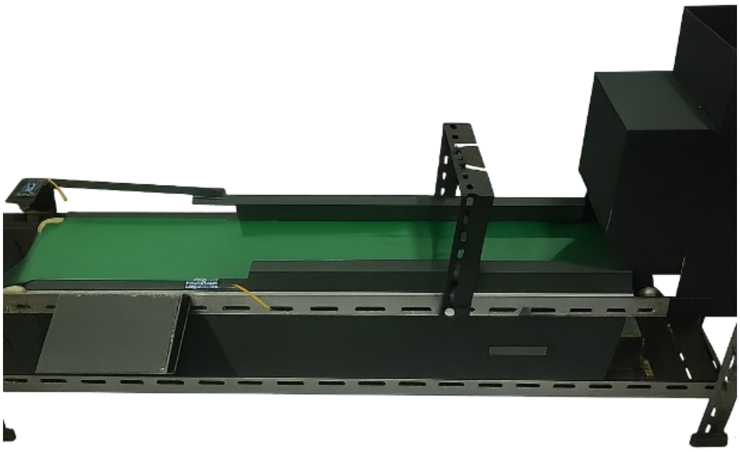


Fig. 3. Mechatronics Sorting System

Table 4. Mechatronics Implementation

Orange Queue	Ripe Divide
1	Correct
2	Correct
3	Correct
4	Correct
5	Correct
6	Correct
7	Correct
8	Correct
9	**Wrong**
10	Correct
11	Correct
12	Correct
13	**Wrong**
14	Correct
15	Correct
16	Correct
17	Correct
18	Correct
19	Correct
20	Correct

4. Conclusion

This research confirms that HSV color segmentation is a highly effective and viable method for the non-destructive, automated sorting of oranges based on maturity. The research provides a validated set of optimal HSV parameters and a functional system design that can be further refined, particularly by improving lighting consistency and material handling, to achieve even higher operational reliability in industrial applications.

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