Automated Lettuce Grading and Sorting in Postharvest Manufacturing Setup

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***Abstract*— In the Philippines, iceberg lettuce *(Lactuca sativa var. capitata)* remains a high-value crop but its postharvest handling remains inefficient, relying heavily on manual grading and sorting. This study developed a vision-based quality grading and sorting system to streamline postharvest processes. The system utilized MATLAB for control logic and computer vision integration, enabling precise automation into three sorting bins corresponding to the grade of the iceberg lettuce. Computer-aided design and dimensioning were carried out using Fusion 360, ensuring the conveyor system design met operational and spatial constraints specific to the lettuce postharvest handling requirements. The automated sorting conveyor which handles five (5) lettuce heads per batch, demonstrated 100% precision at 70% speed and 92% at full operational speed. System time studies recorded an average cycle time of 7.5 seconds per lettuce and a throughput time of 8 lettuces per minute, confirming the system's efficiency and suitability for postharvest operations.**

Keywords—iceberg lettuce, quality grading, vision-based sorting, precision agriculture, postharvest automation

I. INTRODUCTION

In the Philippines, Lettuce (*Lactuca Sativa*) is a crop of high value, which mainly grows in the colder regions of Luzon like, Benguet and Mountain Provinces [1]. Open-field technologies are prevalent in the country where lettuce varieties of higher caliber are unable to be sold on spot markets due to high investment costs to maintain cultivation and low marketing channels [2]. This inability to differentiate high quality produce from iceberg lettuces results to 20-30% losses due to improper sorting and trimming [3]. One key area for improvement in postharvest lettuce handling is the grading and sorting process, which ensures produce is marketed based on size, color, and freshness [4]. These tasks are still performed manually by farmers, leading to inconsistent quality and reduced market competitiveness [5]. Improving this process through automation will support Filipino lettuce growers in meeting market demands [6] [7].

Current research trends on sorting and grading within the agri-food sector emphasize its sensing, smart and sustainable (S3) domains [8]. Literature has emphasized the use of computer vision techniques to address vegetable quality based on color, size, and internal quality parameters as its sensing domain [9]-[12] Most common sensing devices for computer vision relies on extraction of color spaces from a charge-coupled device (CCD) cameras placed on an artificially illuminated chamber that will then provide quality parameters based on physiochemical properties of the crop [13]. Studies have also employed an evaluation or grading criteria as basis for their grading and sorting methods [14]. Recent developments in lettuce quality classification have been focused on lettuce freshness based on chlorophyll-*a* concentrations, moisture content, and fresh head weight [15]-[17]. The use of microcontrollers with the inferencing done on a computer has been the primary setup for the smart domain of the agri-sorting system, where open-source hardware like that of Arduino and the use of programmable logic controllers are used to execute sorting with minimal human oversight. [18]-[21]. Lastly, sustainable domains aim to reduce costs while ensuring robust and repeatable sorting throughout their use-life [22]. Many studies consider accuracy, repeatability, and throughput time to be the main performance metrics for a grading and sorting system in comparison to conventional methods within agri-food industries. Many studies consider accuracy, repeatability, and throughput time to be the main performance metrics for a grading and sorting system in comparison to conventional methods within agri-food industries [23]-[24]. .

Despite the trends in postharvest handling, there are still minimal studies that cover grading and sorting for iceberg lettuce. Subjectivity of quality of iceberg lettuce within local markets makes ambiguous classification during manual sorting in local farms. Standards have provided a framework for uniform compliance with domestic market requirements but are not applied and integrated within the local agricultural sector [25]. This perpetuates reliance on manual sorting practices that are not in line with metrics mentioned in standards [26]. Addressing this gap requires bridging qualitative standards with quantitative measurement tools to enhance grading accuracy, reduce waste, and improve market competitiveness.

The main objective of the study is to develop an automated lettuce grading and sorting system for iceberg lettuce that samples five lettuces per batch on a conveyor belt. The basis for sorting is a three-level grading criteria based on chlorophyll-*a* [27]-[28], moisture content [29]-[30] and fresh head weight [31]-[32] with lettuces extracted within two weeks of harvesting.

This study undertakes the development of a specialized lettuce grading system tailored to the Philippine context based on the Philippine National Standard for iceberg lettuce (PNS/BAFPS 19:2005) [33]. It seeks to enhance economic sustainability within the lettuce farming sector by equipping local iceberg lettuce farmers with a grading system and postharvest processing line aimed to increase the supply of high-quality produce in consumer markets, particularly benefiting underserved populations. Improved post-harvest handling practices help maintain fresh produce's nutritional and sensory qualities, ensuring higher-quality food for consumers. Furthermore, the focus on locally sourced produce promotes sustainable agricultural practices, contributing to a more resilient and health-oriented food ecosystem.

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II. METHODOLOGY

The design and construction of the mini-production line needed for the study includes a conveyor belt system, imaging system, control system, and sorting system. This mini-production line is then constructed to test the classifying and grading of iceberg lettuce in terms of its test throughput time and the precision of the sorters, as provided on Figure 1.

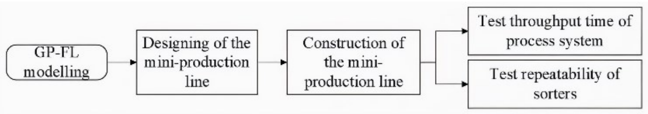

Fig. 1. Simplified block diagram for mini-production line

A. *Genetic Programming-Fuzzy Logic Models*

The system integrates Genetic Programming (GP) for parameter estimation with a Mamdani-Type 1 Fuzzy Logic (FL) inference system for final quality classification. GP models were trained to predict three quantitative quality parameters as mentioned to be chlorophyll-*a* levels, moisture content, and fresh head weight, using RGB-HSV values as inputs. These predicted parameters were then passed into the fuzzy inference system, which classified the lettuce samples into three linguistic grades (L1 – high quality, L2 – medium quality, L3 – low quality) with an overall accuracy grading of 90% with a maximum computational complexity of 496 nodes for the GP models upon training. The code implementation can be checked in the provided git repository: https://github.com/ferds003/Automated-Lettuce-Grading-and-Sorting-in-Postharvest-Manufacturing-Setup.git.

B. *Implementation Procedures*

1) Conveyor and Sorter Arm Design Considerations and Specifications

Two conveyor belts of identical specifications were designed for the mini production line, as these aligned with the objectives of the imaging and sorting requirements, as shown in Figure 2. Both conveyors were powered by a 60W adjustable speed motor, which allowed precise control over belt movement to accommodate different processing speeds. For the handling of the lettuce, the consideration for selecting the specifications for the conveyor belt was that the PVC belt had a width of 20 cm and a thickness of 0.2 cm. It also had a length of 150 cm and a height of 75 cm, which ensured the handling of lettuce was non-invasive. The frame of the conveyor belt was constructed from stainless steel, a material selected for its suitability in food-grade applications.

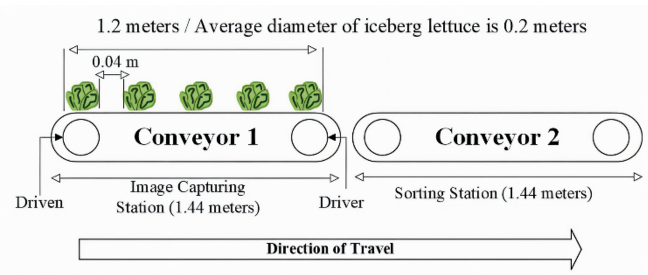

Fig. 2. Visual representation of dimensional requirements for the current setup of the study covering approximately 3 meters in total length.

The imaging chamber was designed in such a way that it provides a controlled environment for accurate image capturing of the iceberg lettuce batches of five (5), as these are transported throughout the image-capture station. For high-quality image acquisition for further processing, the design considerations centered on background uniformity and seamless integration with the conveyor system. Shown in Figure 3 is an isometric CAD drawing of the chamber with dimensions provided in mm. It includes the measurements for the slotted steel angled bars, the dimensions required for the camera placements, and a background wall cover allowing a controlled image-taking environment. This setup allows the system to take images of the lettuce in batches of five, allowing for higher throughput of sorted lettuces.

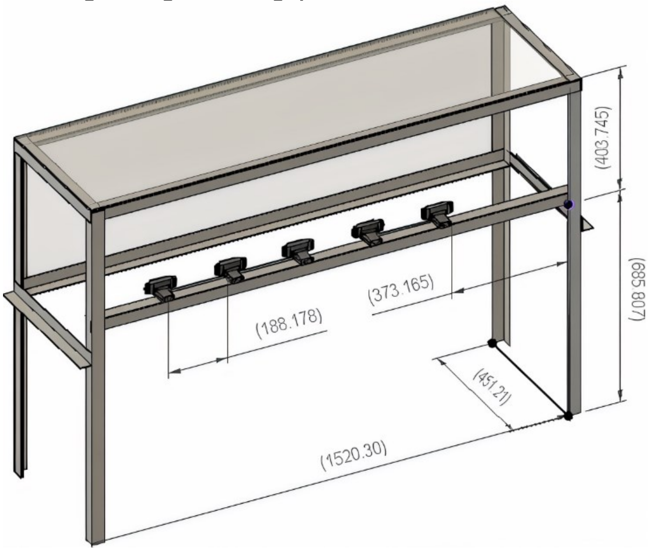

Fig. 3. Isometric CAD Drawing of imaging chamber detailing dimension constraints and placement of 1080p cameras.

A lever arm was designed that would be actuated by the servo motor to guide and sort iceberg lettuce onto its designated sorting bins. The length of the lever arm was based on the width of the conveyor belt. Guide rails were also designed, which would be used to prevent lettuce from falling off the conveyor belt or prevent it from hitting the servo motors during the sorting process, as seen in Figure 4.

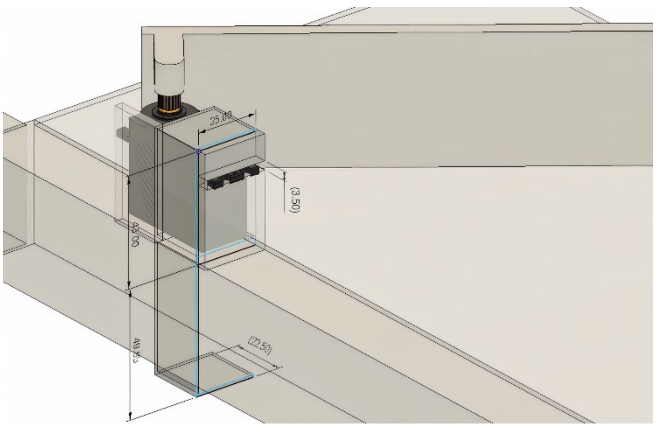

Fig. 4. Isometric view of 3D-printed sorter arm and clamp that is equipped on the MG966R servo motor placed on sorting conveyor-side.

Guide rails were positioned at the start and end of the conveyor, as well as in between designated sorting slots. The lengths of the guide rail varied depending on its placement on the conveyor.

The sorting conveyor consists of the conveyor itself, guide rails, servo motors, servo motor mounts, and servo lever arms. CAD modelling software was used to design the layout of the sorting conveyor's components. All of these components can be seen in Figure 5 below with units in millimeters (mm) along with the dimension constraints. As the lettuce moves from grading to sorting, the actual configuration took into account an additional 100 mm of clearance at the beginning of the sorting conveyor for the space between the two conveyor belts.

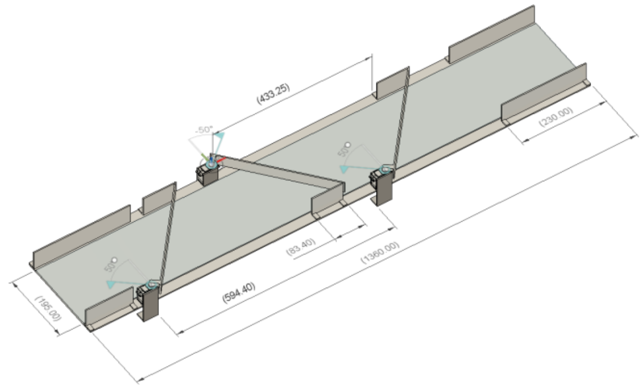

Fig. 5. Isometric CAD drawing of sorting conveyor detailing dimension and angle constraints of servo motors.

2) System Design

Figure 6 shows the process flow of the system, which includes the input of a lettuce to the system composed of an imaging chamber and a sorting chamber, which were captured using multiple cameras and graded accordingly using a genetic programming and fuzzy logic model. Afterwards, the system sorts the lettuce based on the output grade, separating them into different sorting bins.

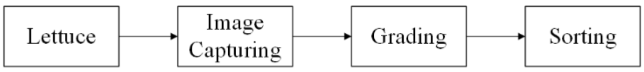

Fig. 6. System process chart

a) Lettuce

The specific variant of lettuce used is the iceberg lettuce (*Lactuca sativa var. capitata*). These lettuces were freshly harvested up to two weeks before the use in the grading and sorting setup. Of these lettuces, there were three with different grading qualities chosen as the ground truth for the setup based on their extracted chlorophyll-*a*, moisture content, and fresh head weight. Figure 7 shows the three lettuces chosen as the ground truth.

(a.) (b.) (c.)

Fig. 7. Ground truth samples of iceberg lettuces procured of (a.) high-quality “L1”, (b.) medium-quality “L2”, (c.) low-quality “L3” respectievely for GP-FL modelling.

b) Image Capturing

Figure 8 shows the image capturing using five (5) 1080p HD Logitech C920 cameras in a single-file line parallel to the conveyor, located in the imaging chamber.

The chamber also included LED lights that output an average of 400 lux across the areas in front of each camera. This ensured that the lettuces are gradable and sortable up to 5 lettuces per batch.

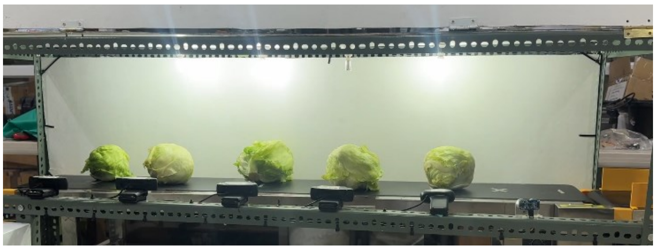

Fig. 8. Camera setup in front of imaging conveyor showcasing placement of iceberg lettuces upon first detection of ultrasonic sensor before sorting.

c) Grading

The grading of the lettuces required the use of a combined genetic programming and fuzzy logic (GP-FL) model. The inputs of the GP were the RGB and HSV color features extracted during the image processing. This gave the lettuce’s moisture content, chlorophyll-*a*, and fresh head weight which the combination of it will be forwarded to FL for grading based on L1, L2 and L3 grades.

d) Sorting

The lettuces were then sorted based on the output grading level, with three sorting bins present for each grade levels: “L1” for high-quality, “L2” for medium-quality, and “L3” for low-quality lettuces. The lettuces were sorted using 3D-printed lever arms attached to a servo motor on the conveyors. Sorting also happens as a staggered release.

3) Evaluation Metrics

The use of time study as a method for measuring the amount of time required by the system to complete the task is a helpful way of analyzing a system’s efficiency. By taking the cycle, theoretical, and throughput times of the system, it became possible to optimize the efficiency of its operations. Equation 1 shows the formula for calculating the average cycle time calculated by the summation of the time it takes to perform each element of a task or process over several observed cycles, then dividing that total by the number of cycles observed

$$\text{Average cycle time} = \sum \frac{\text{Times to perform each element}}{\text{Number of cycles observed}} \quad (1)$$

Normal time is shown in Equation 2, which uses a rating factor as a variable to account for the variance in the performance of the system.

$$Normal\,Time\ (NT) = ACT \cdot Rating\ factor \quad (2)$$

Equation 3 is the formula for calculating throughput time, used for finding the total time it takes for the system to finish all the processes, from inputting the lettuce to the sorting of it.

$$Throughput\ time = \frac{NT}{1 - allowances} \quad (3)$$

Precision is another important metric to consider for the system, as it indicates the effectiveness of the system in the consistent sorting of lettuces for a post-harvest setup. It uses the number of correctly sorted lettuces and divides it by the total number of lettuces sorted to find the precision percentage (%), as shown in Equation 4.

$$Precision = \frac{Correct\ sorting}{Total\ sorting} \times 100 \quad (4)$$

III. Results and Discussion

Figure 9 shows an overview of the fully developed prototype. As mentioned, the system consisted of an imaging chamber with five cameras placed, a sorting conveyor wherein servo motors were responsible for sorting, and baskets that acted as containers for the sorted lettuces. Located on the left side was the control box responsible for connecting every electronic and electrical part together, with the Arduino, circuit breaker, power supply, and other electronic components inside the box.

Fig. 9. Developed prototype setup featuring mainly the imaging and sorting conveyors equipped with GP-FL grading constructed custom sorting arms.

The throughput time, as shown in Table 1, reveals an inverse relationship between theoretical time and conveyor speed. As conveyor speed increases, the time it takes for lettuce to travel from Camera 5 to the corresponding sorters decreases. This enables higher output per cycle, improving overall system efficiency. The data also suggests that higher speeds result in faster actuation of the lever arms, since the lettuce reaches the sorting points more quickly.

TABLE I. Throughput Time Per Station Within Setup

Station	Distance (cm)	Distance (m)	Speed %	Speed (m/min)	Time (Sec)	2nd Actuation Point (Sec)
Conveyor 1	40	0.4	10%	5.33	4.5	-
Camera 5 to Sorter 1	82.5	0.825	10%	5.33	9.29	-
			20%	10.66	6.19	6.62
			30%	15.99	4.64	4.97
			40%	21.32	3.71	3.97
			50%	26.65	3.1	3.31
			100%	53.3	1.69	1.81
Camera 5 to Sorter 2	115.5	1.155	10%	5.33	13	-
			20%	10.66	8.67	9.27
			30%	15.99	6.5	6.96
			40%	21.32	5.2	5.56
			50%	26.65	4.33	4.64
			100%	53.3	2.36	2.53
Camera 5 to Sorter 3	144	1.44	10%	5.33	16.21	-
			20%	10.66	10.81	11.56
			30%	15.99	8.11	8.67
			40%	21.32	6.48	6.94
			50%	26.65	5.4	5.78
			100%	53.3	2.95	3.15

Evinced also in Table 1 is how excessively high speeds can negatively affect the system—causing lettuce to strike the lever arms more forcefully, which may reduce product quality and lead to inaccurate or imprecise sorting.

Table 2 shows the precision of the sorting setup with 70% conveyor speed, from which five different lettuce samples of five trials were done. The GP-FL model's grade was compared with the sorter that the lettuces were sorted in, which overall led to a precision of 100%, indicating that, over all the runs done by the setup, the sorter was precise and consistent in its sorting to the correct quality.

TABLE II. Precision Test Using 70% Conveyor Speed

# No.	Trial #1		Trial #2		Trial #3		Trial #4		Trial #5	
	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in
1	L1	L1	L1	L1	L3	L3	L2	L2	L3	L3
2	L2	L2	L2	L2	L3	L3	L1	L1	L3	L3
3	L3	L3	L1	L1	L1	L1	L3	L3	L2	L2
4	L1	L1	L3	L3	L1	L1	L2	L2	L2	L2
5	L2	L2	L3	L3	L2	L2	L1	L1	L3	L3
									Precision	**100%**

Table 3, meanwhile, is the precision test when the conveyor speed is increased to 100%. Unlike the 70% conveyor speed, the table shows that there are inaccuracies when sorting while the conveyor is at full speed, such as in sample number 2 on trial 1, wherein the model predicted a grade of low quality, but was sorted to the medium quality bin. This indicates a less consistent setup due to performance issues, so operating at a lower conveyor speed is adequate for a consistent sorting system.

TABLE III. Precision Test Using 100% Conveyor Speed

# No.	Trial #1		Trial #2		Trial #3		Trial #4		Trial #5	
	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in	GP-FL Grade	Sorted in
1	L2	L2	L1	L1	L2	L2	L3	L3	L1	L1
2	L3	L2	L2	L1	L3	L3	L1	L1	L2	L2
3	L1	L1	L1	L1	L2	L2	L2	L2	L3	L3
4	L2	L2	L2	L2	L3	L3	L1	L1	L3	L3
5	L1	L1	L3	L3	L2	L2	L1	L1	L2	L2
									Precision	**92%**

IV. Conclusion

The setup with a total length of 3 meters is very suitable for small-scale farm operations with limited space often mentioned by local lettuce producers hindering automation in postharvest handling. With that intention, the study was able to develop a grading and sorting system for postharvest iceberg lettuce capable of handling 5 head per batch for inferencing for sorting based on three-level grade criteria with an evaluation on its throughput time and repeatability. This paper was able to demonstrate that the developed sorting conveyor system achieved 100% precision at 70% speed, and

92% repeatability at 100% speed, based on five trials for each speed setting.

A limitation of the study is the lack of sample size from the GP-FL modelling down to the repeatability trials. We urge future works to consider at least a sample size of 30 for all analysis. Future studies should also consider comparative analysis from traditional vs. the current setup to determine its sustainable domain advantages.

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