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Development of Strawberry Harvest Support System Using Smart Glasses

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Abstract— **The strawberry industry faces significant challenges such as harvest inefficiency and inconsistent quality due to labor shortages and reliance on inexperienced workers. One factor contributing to this is the lack of quantified criteria for strawberry harvesting decisions. In this study, we propose a harvest support system that uses smart glasses as a medium to provide real-time feedback on quantified ripeness and size information through computer vision technology. In the experiment, we compared the efficiency and accuracy of harvesting between cases where humans made harvesting decisions alone and cases where they were supported by the developed system to verify the usefulness of the developed system. The results showed that the system improved the harvesting speed by 17%, the accuracy of size evaluation by 25% and ripeness evaluation by 8% compared to the case where only human judgment was used. These results suggest that this system not only improves productivity and ensures consistent quality but also is expected to increase the number of new entrants in the strawberry industry, potentially addressing the labor shortage in the strawberry sector.**

I. INTRODUCTION

Globally, the agricultural sector faces a significant labor shortage due to demographic shifts [1], including aging populations and urban migration. This shortage of skilled farmworkers has forced many industries to depend increasingly on less experienced and temporary labor, leading to inefficiencies and compromised crop quality across various regions [2]. In response, numerous countries are exploring strategies to mitigate these labor challenges. One prevalent approach involves embracing technological innovations such as automation, robotics, and artificial intelligence. These technologies aim to improve farming efficiency and reduce reliance on human labor [3], [4]. Governments and private sectors are investing in smart agriculture solutions [5], positioning agriculture as a high-tech industry and potentially attracting a younger workforce, thereby securing a sustainable future for the sector.

Over the years, significant advancements have been made in the field of agricultural technology, particularly in the development of automation and monitoring systems for strawberry cultivation [6], [7]. Research has progressively focused on robotic solutions for strawberry harvesting, leveraging sophisticated algorithms and mechanical innovations to improve efficiency and reduce labor dependency. For instance, studies by Xiong et al. [8] and Peng et al. [9] have demonstrated the effectiveness of robotic harvesters that utilize computer vision and deep learning techniques to identify and pick ripe strawberries, showcasing substantial advancements in robotic agility and decision-making capabilities. Concurrently, Yu et al. [10] and Xiong et al. [11] have contributed to this domain by refining the mechanics and sensory systems of these robots, ensuring delicate handling and precision in harvesting operations. These automated solutions aim to provide consistent, quantifiable criteria for harvesting, potentially addressing the variability introduced by inexperienced workers. However, they often come with significant limitations, such as high implementation costs and bulky equipment that can be challenging to deploy in diverse field conditions, making them inaccessible to many farmers.

In addition to robotics, there has been a surge in the development of smartphone applications and IoT-based systems aimed at optimizing strawberry production through real-time monitoring and data analysis. The integration of IoT technology with cloud computing allows for the continuous monitoring of crop health and environmental conditions, facilitating proactive management practices. Research by Park et al. [12] and Cruz et al. [13] exemplifies how IoT devices can be used to create a comprehensive data-driven framework for managing and predicting agricultural outputs. Furthermore, smartphone applications, as discussed by Yue et al. [14] and Toda et al. [15], provide user-friendly interfaces for farmers to access and interpret complex data, making technology more accessible and applicable at the ground level. While these solutions offer valuable insights and can help standardize some aspects of crop management, they present practical challenges in the field, especially during harvesting. Smartphones need to be carried and often held in hand, which can be cumbersome and impractical during hands-on tasks such as harvesting, where workers typically need both hands free for efficient picking. Moreover, while these apps provide useful data, they may not offer the immediate, hands-free guidance necessary for inexperienced workers during the critical task of selecting and harvesting ripe strawberries.

The persistent challenge in strawberry farming lies in the intersection of reliance on inexperienced workers and the absence of established quantification criteria for harvest operations. Traditional methods, even when supported by technological tools, still heavily depend on human decision-making for identifying ripe strawberries and determining the optimal time for harvesting. This dependence becomes particularly problematic when the workforce lacks the nuanced

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skills necessary for effective crop management and harvesting. The absence of clear, measurable standards complicates the assessment of optimal harvest timing and techniques, leading to inefficiencies and inconsistencies in production when relying on inexperienced workers, as they have no standardized benchmarks to guide their decisions.

To address these interconnected challenges, an innovative approach leveraging smart glass technology in agriculture has emerged as a promising solution. Smart glasses, equipped with augmented reality (AR) capabilities and integrated computer vision systems, offer a unique combination of hands-free operation and real-time data visualization directly in the worker's field of view. Recent research by Ponnusamy et al. [16] demonstrates the efficacy of smart glasses in providing instantaneous feedback on leaf disease, thereby enhancing early detection and management of crop health issues. Furthermore, Huuskonen et al. [17] discussed the potential of smart glasses to significantly augment workers' efficiency in various on-farm daily activities highlighting the advantages of clear and rapid data visualization. These studies collectively underscore the potential of smart glass technology to revolutionize agricultural operations, offering solutions to the dual challenges of labor shortages and the need for consistent, quantifiable criteria, particularly in labor-intensive crops such as strawberries.

In light of these findings, we proposes a harvest support system that utilizes smart glasses to provide real-time feedback on strawberry ripeness and size directly to workers in the field. This system utilizes computer vision technology to assess and quantify the ripeness and size of strawberries, offering guided information through a wearable interface. Unlike bulky automation systems or handheld smartphones, smart glasses can be comfortably worn on the head, allowing workers to maintain full dexterity for harvesting tasks while receiving crucial information.

II. STRAWBERRY HARVEST SUPPORT SYSTEM

A. *SYSTEM CONFIGURATION*

This paper presents a harvest support system designed to provide real-time assistance to workers during strawberry harvesting by offering information about fruit ripeness and size. Fig. 1 illustrates the practical application of this system in a real-world harvesting scenario, demonstrating its integration into the strawberry harvesting process.

The harvest support system comprises two primary hardware components that work in concert to provide real-time feedback to agricultural workers. This system utilizes a configuration consisting of smart glasses (Moverio BT-45C, Seiko Epson Corporation) and a GPU-enabled notebook computer (Alienware x16 R1, Dell Technologies Inc.).The smart glasses, which constitute the first key component, serve a dual function within the system. They act as both an image capture device and a display unit. This dual functionality enables workers to receive visual feedback without hindering their manual tasks, thereby preserving the hands-free nature of conventional harvesting techniques. The implementation of smart glasses represents a significant advancement over previous technologies, such as smartphones or tablets, which necessitate manual manipulation and may interfere with the harvesting process. The second hardware component, the notebook computer, functions as the system's primary processing unit.

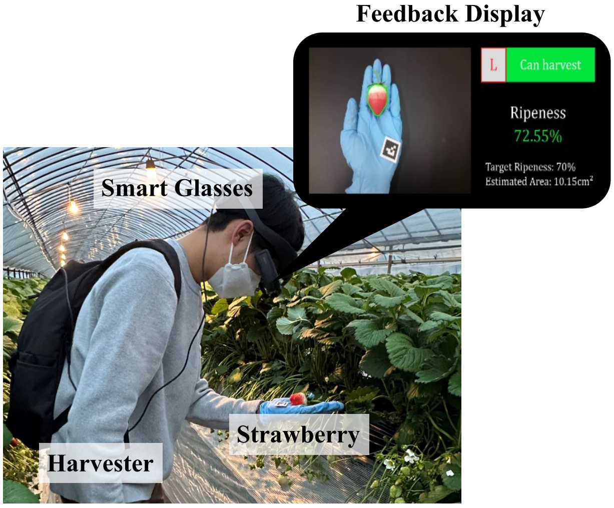

Fig. 1. Practical application of harvest support system

Fig. 2 presents a comprehensive illustration of the system's operational flow. The process begins with the smart glasses capturing images of strawberries within the worker's field of view. These images are then transmitted to the notebook computer for processing. In the context of strawberry harvesting, workers must first identify and assess individual fruits to determine their suitability for harvest. Consequently, the initial step in the processing pipeline involves the extraction of the hand area, which is accomplished using MediaPipe, an open-source framework designed for constructing machine learning pipelines [18]. For strawberries located within this extracted area, color extraction techniques are employed to extract the fruit from its surroundings. Following strawberry extraction, the system applies algorithms to assess the ripeness and size of the fruit. These algorithms, which will be explained in detail in Subsection II-B, utilize the color information and spatial data derived from the image to make these assessments. Upon completion of the ripeness and size assessments, the resulting information is transmitted back to the smart glasses and displayed on the screen, offering immediate feedback to the worker. This feedback typically includes quantitative data on the strawberry's ripeness level and size, presented in an easy-to-understand format allowing workers to make quick and informed decisions about whether to harvest each fruit.

B. *STRAWBERRY ANALYSIS*

The strawberry analysis component of harvest support system employs image processing techniques to assess the ripeness and size of strawberries in real-time. The analysis pipeline consists of 3 stages including strawberry detection, ripeness calculation and size estimation.

The analysis begins with the conversion of the captured

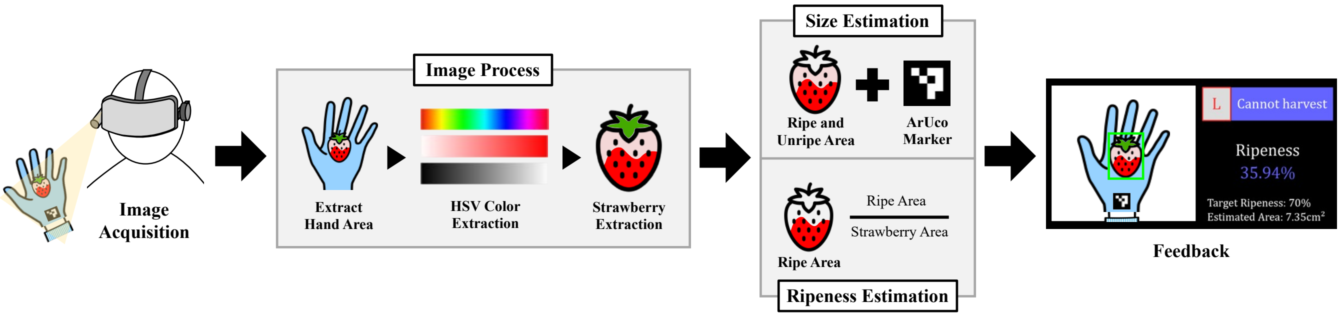

Fig. 2. System operational flow

image from the red, green and blue (RGB) color space to the hue, saturation and value (HSV) color space. The HSV color space is preferred for this application due to its ability to separate color information (hue) from lighting conditions (value) [19]. This separation allows for more robust color-based extraction under varying field conditions, which is essential for accurate strawberry detection across different times of day and weather conditions.

Strawberry detection is achieved using an HSV color extraction method, with specific HSV ranges calibrated to identify both ripe (red region) and unripe (green and white regions) areas of the strawberry. As illustrated in Fig. 3, the HSV ranges used for detecting ripe areas are H: 0-25 and 160-179, S: 60-255, V: 60-255. For unripe areas, the system uses an HSV range of H: 0-80, S: 0-90, V: 90-255. These ranges, determined through careful calibration, may overlap due to the gradual color transition during ripening. To address this overlap, ripeness is quantified as the percentage of the ripe area relative to the total strawberry area using binary thresholding, ensuring a practical and accurate assessment.

In addition to the HSV-based color extraction, blue gloves are used to enhance the robustness of strawberry detection. The gloves address hygiene concerns and improve image processing by creating a clear contrast. This contrast makes it easier to separate each strawberry from the background, allowing the system to reliably identify and segment strawberry, even in complex field conditions.

The extraction process, as depicted in Fig. 3, involves the extraction of ripe and unripe areas of the strawberry. This process is carried out using binary thresholding operations, where pixels falling within the specified HSV ranges are marked in separate binary masks for ripe and unripe areas. These segmented areas are then combined to form a complete representation of the strawberry.

Ripeness calculation is a critical aspect of the analysis. The system quantifies ripeness based on the percentage of the ripe area relative to the total strawberry area. This calculation is performed using Equation (1).

$$\text{Ripeness (\%)} = \frac{A_{ripe}}{A_{ripe} + A_{unripe}} \times 100 \tag{1}$$

A_{ripe} is the area of the ripe area in pixels and A_{unripe} is the area of the unripe area in pixels. Based on this calculated percentage, strawberries are categorized into three ripeness levels: fully ripe (80-100%), half ripe (60-80%) and unripe (below 60%). These categories were established in consultation with experienced strawberry farmers to align with industry standards for harvest readiness.

In addition to ripeness, the system assesses the size of each strawberry, which is another crucial factor in determining harvest readiness and potential market value. The size estimation process involves calculating the total area of the strawberry by summing the pixels in both the ripe and unripe regions of the combined binary mask. An ArUco marker, placed within the camera's field of view, serves as a reference for size calibration. The relationship between pixel area and real-world area is established using Equation (2).

$$\text{Area (cm}^2\text{)} = \frac{A_{ripe} + A_{unripe}}{M_{pixel}} \times M_{real} \tag{2}$$

M_{pixel} is the area of the ArUco marker in pixels and M_{real} is the known real-world area of the ArUco marker. To minimize

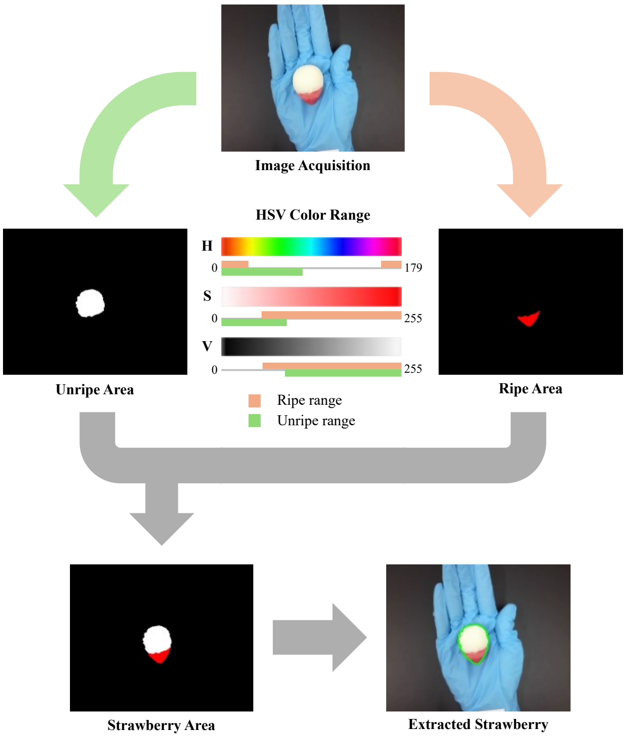

Fig. 3. Strawberry extraction based on HSV color range

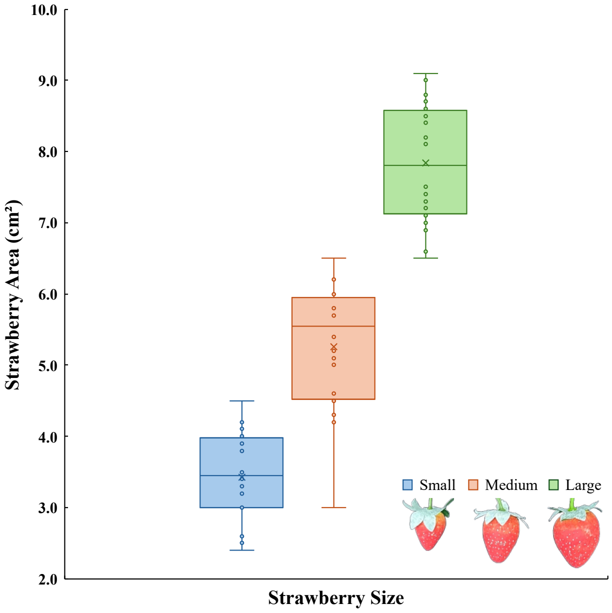

Fig. 4. Strawberry size distribution

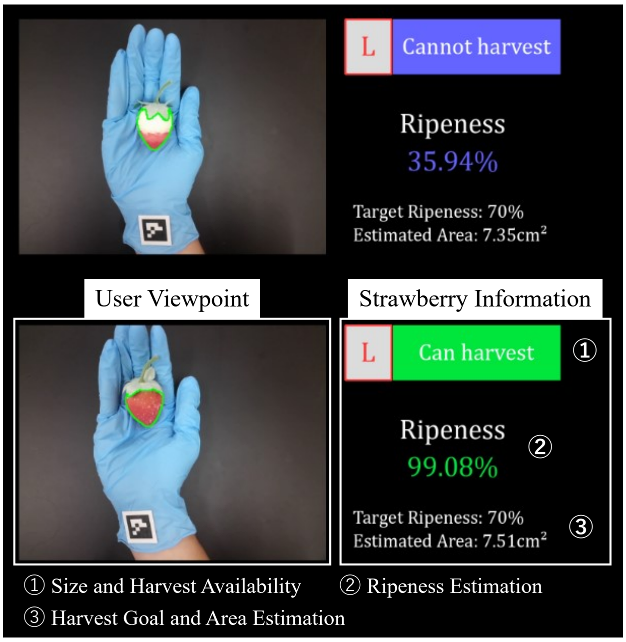

Fig. 5. System interface

size estimation errors caused by distance variations, the ArUco marker is positioned close to the strawberry, ensuring both are at nearly the same distance from the camera. This setup reduces potential distortions, as the minimal distance difference between the marker and the strawberry prevents significant errors and maintains accurate size calibration, even with minor variations in camera positioning.

To establish size categories that align with industry standards and farmer expertise, a calibration process was conducted. A sample of 20 strawberries for each size category (small, medium and large), as determined by experienced farmers' visual inspection, was collected and measured using both the developed system for validation. The average size and standard deviation for each category were calculated and visualized in a box and whisker plot, as shown in Fig. 4. The boundaries between size categories were set at the midpoints between the average sizes of adjacent categories.

C. *USER INTERFACE*

The user interface of the strawberry harvest support system plays a crucial role in effectively communicating critical information to the harvesters in real-time. As illustrated in Fig. 5, the interface provides a comprehensive yet easily digestible display of information, including the strawberry's size, ripeness, and harvest availability status.

The layout of the user interface is strategically organized to prioritize the most critical information for harvest decision-making. Positioned in the top right corner of the display are the size classification of the strawberry and its harvest availability status. This prominent placement ensures that harvesters can quickly assess whether a strawberry meets the size criteria for picking. Immediately below this information, the interface presents the ripeness data, providing a quantitative measure of the fruit's maturity. This arrangement of information allows harvesters to make rapid, informed decisions about whether to pick a particular strawberry based on both its size and ripeness.

In addition to the current state of the strawberry, the interface also provides contextual information to aid in decision-making. The display includes the target ripeness percentage, which serves as a reference point for harvesters. This target value helps workers quickly compare the current ripeness of a strawberry to the ideal harvesting condition.

III. EXPERIMENT

To evaluate the efficacy of the developed strawberry harvest support system, an experiment was conducted. The primary objective of this experiment was to quantitatively assess the impact of the harvest support system on the speed and accuracy of strawberry harvesting decisions. The experiment was structured to compare performance metrics between traditional visual assessment and the augmented assessment facilitated by the harvest support system. The experiment employed a within-subjects approach, where each participant performed the assessment task under two conditions: with and without the harvest support system. To mitigate potential order effects and reduce bias, the sequence of these conditions was alternated between participants [20]. This counterbalancing strategy ensures that any learning effects or fatigue are distributed across both experimental conditions, enhancing the validity of the comparison [20].

The experimental procedure involved presenting 10 strawberries to each participant, one at a time to simulate the actual harvest process. These strawberries were randomly selected to represent a diverse range of sizes and ripeness levels, reflecting the variability typically encountered in field conditions. For each strawberry, participants were tasked with determining its size and ripeness. The time taken to reach a decision for each strawberry was recorded, along with the accuracy of the size and ripeness assessments. A total of 10 individuals participated in the experiment, providing a sample size sufficient for meaningful statistical analysis while remaining feasible within the constraints of the study. The mean age of participants was 24 years old (SD = 2.36). All participants provided written informed consent prior to their involvement in the experiment. It is noteworthy that this study received ethical approval from the Faculty of Medicine Ethics Committee at Saga University, Japan, under Application No. R4-38, ensuring adherence to established ethical standards for human subject research.

IV. RESULTS AND DISCUSSIONS

The experimental results, visualized through box and whisker plots in Fig. 6 and 7, provide compelling evidence of the effectiveness of the harvest support system in enhancing strawberry harvesting efficiency and accuracy. These plots illustrate the distribution of performance metrics across participants for both conditions, with percentage improvements calculated based on the mean values of these metrics across all participants.

Fig. 6 presents the distribution of average time taken to assess each strawberry. The data reveals an improvement in decision-making speed when participants utilized the harvest support system, with an average reduction in assessment time of 17% compared to unassisted human judgment. This increase in efficiency can be attributed to several factors. Primarily, the real-time display of quantitative data regarding ripeness and size eliminates the need for subjective estimation, allowing harvesters to make quicker decisions. Additionally, the consistent presentation of information likely reduces cognitive load, enabling faster processing and decision-making.

The average accuracy of size evaluation, depicted in Fig. 7, shows a improvement of 25% when using the harvest support system. This increase in size assessment accuracy can be explained by the system's ability to provide precise, quantitative measurements based on computer vision algorithms and ArUco marker calibration. Human perception of size can be influenced by individual judgment variability. The system mitigates this issue by offering standardized, objective measurements, leading to more consistent and accurate size evaluations.

Fig. 7 illustrates the average accuracy of ripeness evaluation, which improved by 8% with the assistance of the harvest support system. While this improvement is more modest compared to the gains in speed and size accuracy, it remains significant. The smaller margin of improvement in ripeness assessment might be attributed to the fact that experienced harvesters often develop a keen eye for judging ripeness based on color. However, the system's ability to quantify ripeness percentage provides an objective measure that can be particularly beneficial in edge cases or for less experienced workers. The improvement also suggests that the system helps standardize ripeness assessment across different individual perceptions.

While the overall trend shows improvement, it should be noted that some participants exhibited lower speed and accuracy when using the harvest support system. This phenomenon can be attributed to several factors. Firstly, there may be a learning curve associated with interpreting the information displayed on the smart glasses. Participants who were less familiar with such technology might have initially found it challenging to integrate the displayed information into their decision-making process, leading to slower performance. Secondly, some participants may have experienced a form of cognitive overload, where the additional information

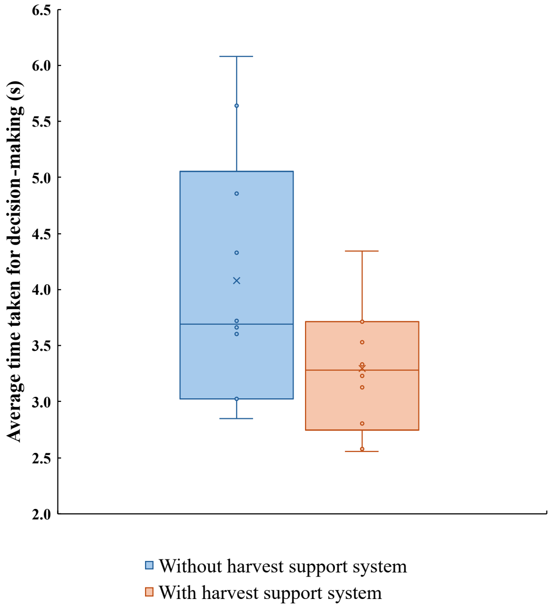

Fig. 6. Distribution of average time taken for decision-making

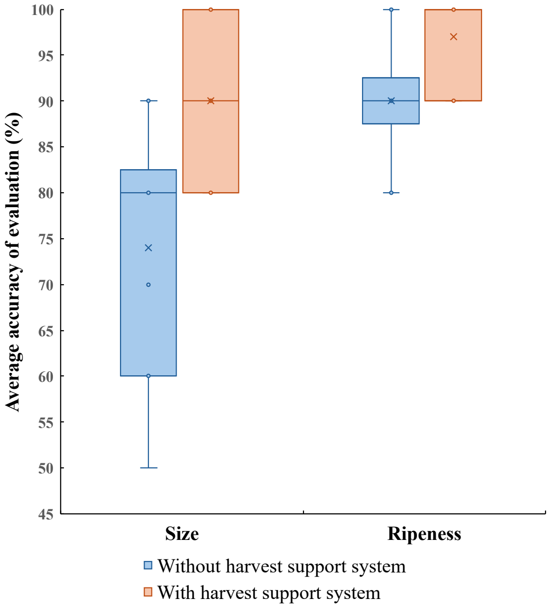

Fig. 7. Distribution of average accuracy for size and ripeness

initially slowed down their decision-making process as they attempted to reconcile the system's data with their own perceptions. Furthermore, individual differences in adapting to new technologies could play a role. Some participants might have felt more comfortable relying on their traditional methods of assessment, leading to hesitation or double-checking when presented with the system's data. This behavior could result in increased assessment times and potentially impact accuracy if participants second-guessed their initial judgments.

Despite these individual variations, the overall improvements in speed and accuracy demonstrate the potential of the harvest support system to enhance strawberry harvesting operations. The gains in size evaluation accuracy and decision-making speed are particularly noteworthy, as they address two critical aspects of efficient harvesting such as selecting appropriately sized fruits and doing so quickly to maximize productivity. The more modest improvement in ripeness evaluation accuracy suggests that while the system provides valuable assistance, it complements rather than replaces human expertise in this area.

V. CONCLUSIONS

This study introduced and evaluated a harvest support system designed to address challenges in strawberry harvesting. Through experimentation, we demonstrated the system's capacity to enhance both the efficiency and accuracy of harvesting decisions. The results revealed a 17% reduction in assessment time, a 25% increase in size evaluation accuracy, and an 8% improvement in ripeness assessment accuracy when using the system. These findings underscore the potential to transform traditional agricultural practices, offering a promising solution to persistent challenges such as labor shortages and inconsistent product quality in the strawberry industry.

Moreover, this system serves a dual purpose by not only assisting experienced workers but also acting as an educational tool for inexperienced farmers. By providing real-time, quantitative feedback on strawberry characteristics, it standardizes harvesting practices and accelerates skill development. This dual functionality may positions the system as a valuable asset in addressing both immediate productivity concerns and long-term workforce development in the agricultural sector.

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