Method for Ripeness Classification of Harvested Strawberries using Hue Information of Images Acquired After the Harvest

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***Abstract*—Hakata Amaou is the most popular strawberry in Fukuoka Prefecture. However, Amaou farmers face a significant challenge due to a shortage of labor and successors, primarily caused by an aging workforce. This labor shortage is particularly severe during the harvest season, when work must be completed within a short timeframe. To address this issue, INAK System Co., Ltd. has developed an automatic harvesting system called "Robotsumi," which utilizes image recognition technology. Despite this advancement, the current image recognition method has not yet been able to classify the Amaou strawberries into 10 quality grades. Additionally, the image recognition process is affected by image defects, varying light conditions, and shadows. To overcome these challenges, this study first conducted questionnaires to gather information on the ripeness of harvested strawberries as classified by humans. Based on the questionnaire results, maturity classifications using modes of hue were performed. The discrimination results are verified and reported here.**

Keywords—Amaou; Robotsumi; hue; strawberry; automatic harvest; 10 grades classification; questionnaire; image defects

I. INTRODUCTION

Japan's agricultural sector faces a critical challenge: a declining workforce. The number of core agricultural workers peaked at 1.76 million in 2015 but fell to 1.16 million by 2023, a decrease of 600,000. New farmer entries are also declining, dropping from 57,700 in 2015 to 45,800 in 2022. These trends necessitate solutions that reduce labor needs and make agriculture more accessible to young people, especially those with limited experience [1].

Strawberry production exemplifies the broader agricultural workforce shortage. The national harvest declined from 165,600 tons in 2013 to 161,100 tons in 2022, a 2.7% decrease over ten years [2]. Fukuoka Prefecture, known for its high-quality "Amaou" strawberry variety, is a prime example. The prefecture's strawberry farming workforce shrunk from around 150,000 in 2005 to just 64,000 in 2020 [3]. This decline is particularly concerning in Hirokawa-cho, despite the popularity and high demand for Amaou strawberries [4-6].

The labor-intensive nature of strawberry production, coupled with Japan's declining birthrate and aging population, creates a shortage of willing successors. INAC System Co., Ltd. developed "Robotsumi," an automated strawberry-picking robot, to address this issue [7]. Robotsumi harvests strawberries without touching the fruit itself, using a two-stage blade to cut the stem. While the robot can classify ripeness into four levels (unripe, rather unripe, rather ripe, and ripe), strawberry farmers traditionally categorize ripeness based on experience and intuition, often using a 10-level system [8].

Robotsumi goes beyond simple robotic picking. However, there's a need for more detailed ripeness classification for robots. The current "robo-sampling" approach faces limitations. Sunlight and shadows can affect image recognition, making it difficult for Robotsumi to accurately extract strawberry contours and potentially leading to misclassification [8].

Given these challenges, we aim to develop and validate a strawberry ripeness diagnosis system for robots that functions independently of light or shade. Our approach utilizes techniques like strawberry outline extraction, threshold processing using hue, hue analysis for various ripeness levels, and clustering classification using OpenCV [9-12].

To achieve reliable ripeness classification, we'll present strawberry images to strawberry experts and have them evaluate the ripeness through a questionnaire. This will help us assess the consistency of human evaluations for the same image and establish the robustness of the human evaluation criteria. We will also analyze the correlation between expert evaluations and average strawberry hue values. This will determine how well the machine's hue-based classification aligns with human sensory evaluation of ripeness.

The following sections delve deeper into the research background and related work in Section II, our proposed methodology in Section III, experiment details and results in Section IV, and finally, the conclusion is presented in Section V with concluding remarks.

II. RESEARCH BACKGROUND AND RELATED RESEARCH WORKS

Fig. 1 shows the aging of farmers and the decline in the aging of farmers in Hirokawa-Cho, Fukuoka Prefecture Japan. [3] This is just one example. This situation is common to the other prefectures and all over the Japanese farmers.

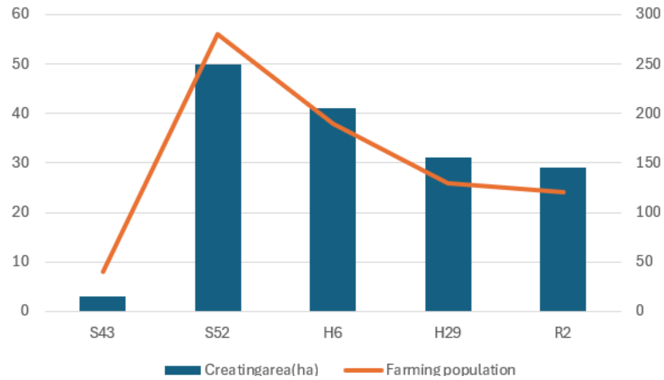


Fig. 1. Number of strawberry farmers and the strawberry planting area in Hirokawa, Fukuoka prefecture Japan [3].

As previously discussed, reducing labor needs and lowering the barrier to entry for young farmers, particularly those with limited experience, are crucial for revitalizing the agricultural sector. INAC System Co., Ltd. developed the "Robotsumi" automatic strawberry picking robot to address this challenge [13] reference source for Robotsumi.

Robotsumi utilizes AI to analyze strawberry color and employs a two-stage blade to sever the stem just above it, harvesting the fruit without direct contact (as shown in Fig. 2). Additionally, it can categorize ripeness into four stages: unripe, somewhat unripe, rather ripe, and overripe.

However, the optimal harvest ripeness varies seasonally. While Robotsumi offers some classification, strawberry farmers traditionally rely on experience and intuition, often using a 10-level ripeness scale, for optimal harvest decisions. Therefore, a more nuanced ripeness classification system is needed for Robotsumi.

Furthermore, current Robotsumi image recognition is hampered by sunlight and shadows, making it challenging to accurately extract strawberry outlines, which can lead to misclassification.

As for the related research works, there are the followings,

1) Robotic strawberry harvesting technology: This paper [14] explores robotic strawberry harvesting. They encountered challenges with fruit recognition due to sunlight-induced halation, which they addressed with blackout curtains. However, the results suggest that further improvements in harvest accuracy may be difficult.

2) Basic research on systemization of harvesting and sorting in strawberry production: This research [15] details the development of a robotic harvesting fruit picking hand. Their system can classify based on ripeness, size, and shape, offering five ripeness levels: 0-3, 4, 5-6, 7-8, and 9-10. However, the paper acknowledges that harvesting likely wouldn't occur at immature stages (0-4) and achieving seasonal-specific harvests within the 5-10 range might require further refinement.

3) Fine-Grained ripeness classification with mask R-CNN and region segmentation: This study by [16] proposes a method for classifying strawberry ripeness into six stages. The rapid ripening nature of strawberries highlights the potential benefits of such fine-grained classification based on average color values.

As for the related image classification techniques, Several relevant image classification techniques exist beyond the scope of strawberry ripeness. These include:

1) Polarimetric SAR image classification: This approach utilizes properties of the polarization signature for image classification, as described in study [17, 18, 19].

2) Multispectral image classification: This method leverages independent spectral features chosen through correlation analysis, as presented in [20].

3) Image classification with probability density functions: This technique considers probability density functions based on simplified beta distributions, explored and validated in study [21].

4) Hyperparameter tuning for image classification: Techniques for hyperparameter tuning in image classification are addressed in study [22, 23]. These studies explore using PyCaret and modifying Optuna-tuned results for EfficientNetV2-based image classification, respectively.

(a) Robot arm

(b) Robot at work harvesting

Fig. 2. Robotsumi robot arm and it’s at work harvesting.

This paper describes a technology for robotically harvesting strawberries. In the daytime test, when the fruits were exposed to direct sunlight, halation occurred and the fruits could hardly be recognized. However, we anticipate difficulties in improving harvest accuracy.

III. Proposed Method and Procedure

A. *Strategic Procedure*

Challenges and proposed solution is that sunlight and shade can significantly hinder strawberry recognition for robots. Additionally, the optimal harvest ripeness varies by season, necessitating a more detailed classification system. This research aims to establish a robust and automated method for classifying strawberry ripeness suitable for harvest (levels 5 to 9) that remains unaffected by lighting conditions.

As for the building on human expertise, drawing inspiration from the existing 10-level human classification system, we developed a method focusing on ripeness levels 5 to 10, typically targeted for harvesting. We established classification criteria that align closely with human sensory perception through expert surveys using questionnaires.

It would be better to mitigate lighting effects. To achieve accurate classification and minimize the impact of sunlight and shade, a crucial challenge identified in previous studies, we implemented a strategy to isolate the strawberry fruit region within the image. Furthermore, we leveraged hue analysis to minimize the influence of lighting variations on the classification process.

Validating the classification system is as follows:

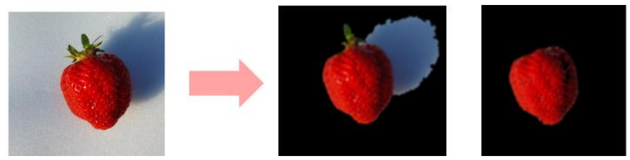
We compared the ripeness classifications obtained through our proposed method with those from the expert questionnaire survey. The results demonstrated a high degree of agreement, validating that our method effectively replicates human sensory perception of ripeness.

As for the basic research on systemization of harvesting and sorting in strawberry production, this paper describes the development of a robotic harvesting hand (see Fig. 3). While it offers ripeness, size, and shape classification with five levels (0-3, 4-5, 6-7, 8-9, and 10), it acknowledges that harvesting likely wouldn't occur at immature stages (0-4) and highlights the need for finer classification within the 5-10 range for seasonal optimization.

Fig. 3. Mobile strawberry harvesting robot [24].

Research procedure is as follows,

1) Extracting fruit from images: The following methods, Contour extraction using Watershed and Hue threshold processing are used. Namely, contours are extracted from the original image using the Watershed algorithm.



(a) Original image (b) Contour by Watershed (c) Threshold with hue.

Fig. 4. Process flow of the proposed method.

As for the fruit segmentation and hue thresholding, to isolate the strawberry fruit for analysis, we first extract the fruit region from the image. We then employ hue threshold processing to further refine the segmentation. A key challenge in this process is to minimize the influence of strawberry stems, shadows, and non-fruit regions (as illustrated in Fig. 4). Hue analysis plays a crucial role in achieving accurate fruit segmentation.

2) Ripeness classification questionnaire implementation: We implemented a questionnaire to gather expert evaluations of strawberry ripeness. The target audience comprised eight strawberry experts from various backgrounds, including INAC System Co., Ltd. collaborators, strawberry farmers, and local research institutes. Participants were presented with strawberry images (see Fig. 5) and asked to select the corresponding ripeness grade. To minimize any potential bias due to image orientation, the strawberry images were presented with rotations of 90 degrees.

Fig. 5. Questionnaire for strawberry quality evaluation.

For ensuring expert agreement (to ensure reliable ripeness classifications from the experts), we conducted the questionnaire twice to improve response consistency. We then calculated the correlation between the two sets of responses from each participant. Only responses from subjects with high correlation coefficients (0.7 or higher) were used for image classification based on maturity classification results.

3) Hue analysis for objective ripeness classification: We conducted a hue value analysis of strawberry images based on the expert ripeness classifications. For each fruit, we calculated the average hue value and measured several key features:

First mode (peak value in the hue distribution)

Second mode (secondary peak value)

Histogram center of gravity (average hue value)

Unripe rate (percentage of pixels with hue values between 100 and 114)

Next, we performed an analysis of variance (ANOVA) using the hue values. This analysis compared the average hue values for each expert-assigned ripeness group (5 to 9) to statistically determine if there were significant differences between the groups.

Finally, we conducted a more detailed hue value analysis for each ripeness level, examining the distribution using methods like:

Mode distribution

Boxplots (visualizing data quartiles)

Scatterplot matrix (showing pairwise correlations between hue and other features)

Clustering (grouping similar hue values)

IV. Experiments

A. Maturity Classification Questionnaire

To establish ripeness classification criteria aligned with human perception, we conducted a questionnaire with eight strawberry experts from diverse backgrounds, including INAC Systems, strawberry farmers, and local research institutes. The questionnaire was administered twice: once in a standard format and again with the same image rotated by 90 degrees. This repetition aimed to verify that participants based their judgments on consistent criteria regardless of image orientation, thereby enhancing the questionnaire's reliability.

We calculated the correlation between each participant's responses from both questionnaires. Only responses with a high correlation coefficient (0.7 or greater) were used to define the ripeness classification criteria. Specifically, we adopted the average of the ripeness classifications provided by the seven experts who achieved high correlation.

Results from the hue value analysis and correlation with expert classification is as follows,

Fig. 6 depicts the relationship between the expert-assigned ripeness classifications and the classifications derived from our hue value analysis.

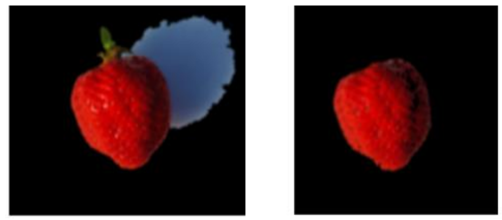
Ripeness	5	6	7	8	9
Average	107.99	112.82	115.08	116.88	117.68
1st Mode	105.50	114.61	116.71	114.61	105.5
2nd Mode	108.00	114.06	117.14	117.86	118.33
Histogram Gravity	108.49	113.32	115.59	117.38	118.18

Fig. 6. Relation between the result from the questionnaire and the classified result with hue.

B. Strawberry Extraction from Image

The first step involved extracting the strawberry fruit region from the image, a crucial element for accurate ripeness classification. We employed a Gaussian filter to reduce noise and facilitate segmentation. Next, a Watershed algorithm was utilized to generate a preliminary outline of the strawberry.

However, the initial segmentation might include unwanted elements like lint and shadows. To address this, we implemented a hue thresholding process that leverages the inherent property of hue being less susceptible to lighting variations. This additional processing resulted in a more refined segmentation isolating only the strawberry fruit itself (as illustrated in Fig. 7).



(a) Watershed (b) Thresholding by hue

Fig. 7. Contour extraction using watershed and thresholding by hue.

C. Hue Analysis for Mechanical and Rigorous Ripeness Classification

1) Strawberry hue analysis and feature extraction: Building upon the expert ripeness classifications obtained through the questionnaire, we conducted an analysis of strawberry image hue. This analysis aimed to identify features that correlate with the perceived ripeness levels. We extracted several key hue-based features from each fruit:

Hue Mean: Average hue value of the strawberry fruit.

Hue 1st Mode: The most frequent hue value (peak of the hue distribution).

Hue 2nd Mode: The secondary peak value in the hue distribution (if present).

Histogram Center of Gravity: The average hue value across the entire distribution.

Percentage of Unripe Portion: The proportion of pixels within the fruit region classified as unripe based on a predefined hue range (e.g., 100-114).

Table I summarizes the results of this analysis.

2) Observations from hue feature analysis (Table I): Table I reveals a clear trend: The percentage of unripe pixels progressively decreases (in descending order) from ripeness level 5 to 9. Conversely, all other extracted hue features (mean hue, 1st mode, 2nd mode, and center of gravity) exhibit an increasing trend across the same ripeness levels. These observations suggest a potential correlation between hue characteristics and the perceived ripeness stages.

Experts further investigated these trends by statistically comparing the average hue values for each ripeness group (5-9) to determine if the differences were statistically significant.

TABLE I. EXPERT ANALYSIS OF HUE VALUES OF STRAWBERRIES AT THE DIFFERENT STAGES OF RIPENESS

Fruit Hue / Maturity	5	6	7	8	9
mean value	107.99	112.82	115.08	116.88	117.68
first mode	105.50	114.61	116.71	114.61	105.5
second mode	108.00	114.06	117.14	117.86	118.33
histogram center of gravity	108.49	113.32	115.59	117.38	118.18
percentage of immature portion	0.92	0.62	0.34	0.13	0.06

3) Statistical significance and correlation with expert classification: The analysis of variance (ANOVA) revealed statistically significant differences ($p < 0.05$) among all the extracted hue features (hue mean, 1st mode, 2nd mode, center of gravity, and unripe percentage) for the various ripeness levels (5-9). This statistically significant variation strongly suggests a correlation between the hue characteristics and the ripeness classifications assigned by the experts.

4) Detailed hue feature analysis (Fig. 8): To further investigate this correlation, we conducted a more in-depth analysis of the hue features using various visualization techniques: mode distributions, box-and-whisker plots (see Fig. 8), scatterplot matrices, and clustering.

The box-and-whisker plot (Fig. 8) visualizing the average hue values for each ripeness level according to the expert classifications proved particularly useful. As evident from the distinct separation between the boxes in Fig. 8, the hue mean values effectively differentiate between the different ripeness stages.

5) Ripeness classification using hue thresholds: Leveraging the insights from the box-and-whisker plot, we established ripeness classification thresholds based on the hue mean values. For ripeness levels with overlapping hue value ranges, we calculated the percentage of overlap and strategically positioned the thresholds to minimize misclassification. The resulting classification based on these hue thresholds achieved a high correlation coefficient of 0.89 with the expert classifications.

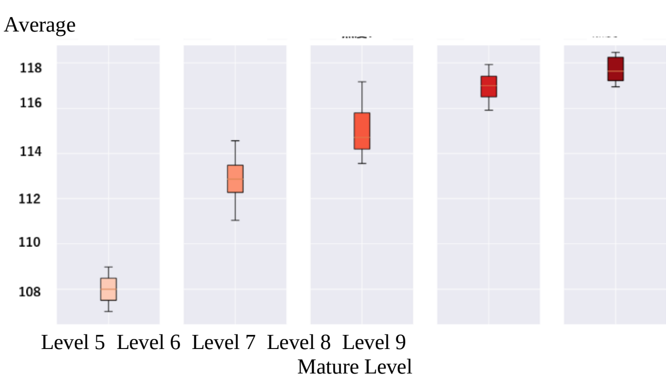


Fig. 8. Box-and-whisker plot of average hue values by maturity according to expert classification.

This demonstrates the feasibility of achieving automated ripeness classification that closely aligns with the perceptions of human experts.

A comparison between classification based on hue value and classification by experts confirmed a strong correlation with a correlation coefficient of 0.89.

Fig. 9 shows the results of hue value analysis for each ripeness level using clustering. From this result, it is found that ripeness classification can be done with the average value of hue derived from the acquired images of strawberries.

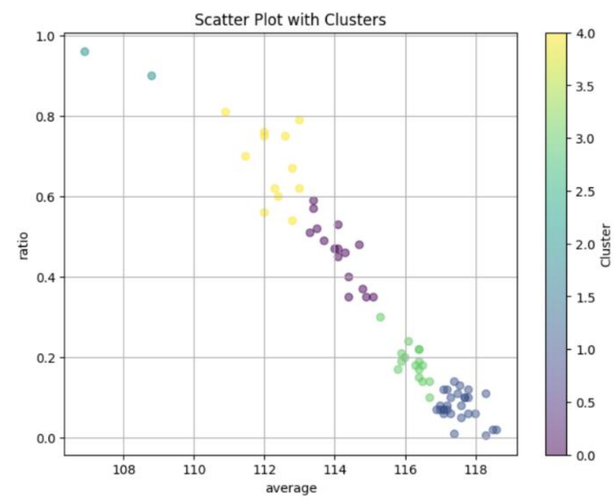


Fig. 9. Results of hue value analysis for each ripeness level using clustering.

V. CONCLUSION

This research aimed to establish a robust and automated method for classifying strawberry ripeness that aligns with human perception. Here's how we achieved this:

1) Expert-informed classification criteria: We conducted a questionnaire with strawberry experts to gather reliable ripeness classifications, serving as the foundation for our automated system.

2) Light-independent fruit segmentation: To isolate the strawberry fruit region for analysis, we employed hue analysis, a technique less susceptible to lighting variations. This facilitated accurate extraction of the fruit from the image, minimizing the influence of light and shade.

3) Hue-based ripeness classification: We analyzed the hue characteristics of the extracted fruit regions. This analysis revealed a correlation between average hue values and the ripeness levels assigned by the experts. Leveraging this correlation, we developed a method for classifying ripeness based on hue thresholds.

4) Validation with expert classification: The ripeness classifications achieved through our automated hue-based method exhibited a high correlation coefficient (0.89) with the expert classifications from the questionnaire. This demonstrates the effectiveness of our system in replicating human sensory perception of strawberry ripeness.

FUTURE RESEARCH WORKS

As a future task, we plan to develop a system that can perform automatic ripeness classification based on this method. Furthermore, when the system is completed, we plan to actually implement it in "Robotsumi" to verify the method and conduct experiments.

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Kohei Arai, He received BS, MS and PhD degrees in 1972, 1974 and 1982, respectively. He was with The Institute for Industrial Science and Technology of the University of Tokyo from April 1974 to December 1978 also was with National Space Development Agency of Japan from January, 1979 to March, 1990. During from 1985 to 1987, he was with Canada Centre for Remote Sensing as a Post Doctoral Fellow of National Science and Engineering Research Council of Canada. He moved to Saga University as a Professor in Department of Information Science on April 1990. He was a councilor for the Aeronautics and Space related to the Technology Committee of the Ministry of Science and Technology during from 1998 to 2000. He was a councilor of Saga University for 2002 and 2003. He also was an executive councilor for the Remote Sensing Society of Japan for 2003 to 2005. He is a Science Council of Japan Special Member since 2012. He is an Adjunct Professor of University of Arizona, USA since 1998. He also is Vice Chairman of the Science Commission "A" of ICSU/COSPAR since 2008 then he is now award committee member of ICSU/COSPAR. He wrote 87 books and published 714 journal papers as well as 650 conference papers. He received 66 of awards including ICSU/COSPAR Vikram Sarabhai Medal in 2016, and Science award of Ministry of Mister of Education of Japan in 2015. He is now Editor-in-Chief of IJACSA and IJISA. http://teagis.ip.is.saga-u.ac.jp/index.html.

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