

Semi-Automated Air-Cell Image Measurement and Weight-Loss Monitoring for Non-Destructive Assessment of Egg Freshness During Storage

Mookarin Nookong, Juthamat Wattanacharosroj, Jettanat Changdee,

Pemsini Buaphae and Chawakorn Sri-ngernyuang *

*Department of Food Engineering, Faculty of Engineering and Agro-Industry, Maejo University,
Nong Han, San Sai, Chiang Mai, 50290, Thailand*

*Corresponding Author E-mail: chawakorn_sgn@mju.ac.th

Received: Feb 16, 2026; Revised: Jun 23, 2026; Accepted: Jun 24, 2026

Abstract

Conventional methods for evaluating egg freshness rely heavily on candling, visual inspection, or destructive laboratory tests. These approaches are often subjective, operator-dependent, and difficult to apply consistently in large-scale food production. To address these limitations, this study developed a non-destructive approach for monitoring egg freshness-related changes during storage by combining cumulative weight-loss measurement with image-based air-cell area measurement. A total of 100 eggs were stored under ambient conditions and repeatedly measured at five time points: Day 1, Day 6, Day 11, Day 16, and Day 21. Repeated-measures ANOVA confirmed significant effects of storage duration on egg weight and air-cell area ($p < 0.001$). Cumulative weight loss reached 4.22% by Day 21, while the mean air-cell area increased from 90.6 mm² on Day 1 to 274.7 mm² on Day 21 after skipped air-cell annotations were treated as missing data. Cumulative weight loss showed a significant positive association with air-cell area ratio when individual egg-level observations were analyzed. However, the moderate regression strength indicated that air-cell enlargement was not explained by weight loss alone and may also be influenced by egg-specific factors such as shell structure, shell porosity, and initial egg size. These findings indicate that combining weight-loss monitoring with GUI-based air-cell image measurement can support non-destructive assessment of freshness-related changes in eggs during storage.

Keywords: Egg freshness, Semi-automated measurement, Air-cell area, Weight loss, Non-destructive assessment

1. Introduction

Egg freshness is an important quality attribute that directly affects consumer safety, nutritional value, and product acceptability across the food supply chain [1],[2]. One of the most noticeable internal indicators of egg aging is air-cell enlargement, which occurs as moisture and carbon dioxide are gradually lost through the eggshell during storage. Progressive egg weight loss is also widely used as a quantitative indicator of freshness deterioration [2],[3]. Therefore, freshness-related changes can be monitored using two measurable indicators: air-cell enlargement and gradual weight reduction.

Conventional methods for assessing egg freshness, such as manual candling and destructive laboratory tests, are often subjective, labor-intensive, and difficult to apply in continuous, real-time, and large-scale quality inspection systems [4–6]. These limitations have encouraged the development of objective, non-destructive, and semi-automated evaluation methods for modern food quality control systems [7]. Recent advances in computer vision and low-cost sensing devices have supported the development of non-destructive approaches for food quality assessment. Image-based analysis can extract quantitative features from captured egg images, including air-cell area and shape-related characteristics [4],[8],[9]. At the same time, precision digital weighing systems can provide reliable measurements of mass loss caused by moisture

transfer during egg storage [2],[10]. Combining multiple freshness-related indicators may provide a more robust assessment than relying on a single parameter alone [1],[4].

The combination of image-based descriptors and accurate weighing has been shown to support quantitative assessment of egg quality and freshness-related changes [11]. Therefore, this approach was adopted in the proposed GUI-based semi-automated framework for monitoring egg weight loss and air-cell expansion. Although egg crack detection has also been explored in image-based egg quality assessment, it was beyond the scope of the present study and is considered a potential direction for future development. In this study, a USB camera fitted with a varifocal lens was used to capture internal egg images under controlled illumination conditions to improve air-cell visualization. In addition, a digital weighing system was used to measure changes in egg mass during storage. The same 100 egg samples were stored under ambient conditions and measured at five storage time points: Day 1, Day 6, Day 11, Day 16, and Day 21. Therefore, this study presents a low-cost GUI-based semi-automated framework for non-destructive assessment of egg freshness-related changes during storage.

The scientific contributions of this study are summarized as follows:

- This study provides longitudinal evidence of freshness-related changes by repeatedly

monitoring the same eggs during storage using two complementary non-destructive indicators: cumulative weight loss and image-derived air-cell area.

- The novelty of this work lies in integrating physical mass-loss information with image-derived air-cell development to characterize freshness-related changes within the same eggs over time, rather than relying on a single indicator or cross-sectional measurements.
- Using individual egg-level observations, the study demonstrates that storage duration significantly affects both egg weight and air-cell area. Cumulative weight loss was positively associated with air-cell area ratio; however, air-cell enlargement could not be explained by weight loss alone because of egg-to-egg variation.
- The study advances the methodological evaluation of egg freshness-related changes by applying repeated-measures analysis and by treating non-visible air-cell observations as missing data rather than numerical zero values. This approach reduces statistical distortion and provides more realistic estimates of storage-related changes.

Together, these findings support the use of combined physical and image-derived indicators for non-destructive monitoring of egg freshness-related changes and provide a scientific basis for future development of validated freshness assessment models.

2. Background and Related Work

Recent developments in computer vision and image processing have enabled non-destructive assessment of egg quality by extracting informative features from shell or candling images. Several image-analysis techniques, including edge detection, contour analysis, ellipse fitting, and region-based segmentation, have been used to identify internal structures and estimate geometric features such as air-cell size and yolk shape [9],[12],[13]. For example, Wang et al. [9] demonstrated that yolk and air-cell geometry can be digitally analyzed to support egg freshness estimation. Subsequent studies have shown that image-derived features, when combined with classification models, can support defect detection and egg quality categorization. Compared with manual candling, computer vision-based methods offer advantages in objectivity, repeatability, and consistency. These findings provide a promising foundation for developing GUI-based semi-automated tools for monitoring egg freshness-related changes [8],[12].

In addition to visual indicators, the relationship among egg weight loss, storage conditions, and freshness indices has been widely investigated. Samli et al. [3] reported that egg weight loss increased with storage temperature and storage duration and was

accompanied by decreases in Haugh unit and albumen quality. Quan et al. [14] developed predictive models using egg weight, albumen height, and Haugh unit measured at different storage temperatures to estimate freshness and shelf life. These findings support the use of precision weighing as an effective non-destructive method for monitoring egg aging under different storage conditions [3],[14],[15]. With the rapid development of artificial intelligence, several studies have investigated egg freshness classification using visual, spectral, or multimodal sensor data. Hyperspectral imaging has been combined with regression or classification models for non-destructive prediction of freshness grades and Haugh unit values [5],[6]. Other systems have integrated thermal or visible imaging with deep neural networks to identify air cells and evaluate freshness levels in quail or chicken eggs [8]. Although these techniques can achieve high accuracy, they often require large labeled datasets, computationally intensive model training, and specialized imaging devices, such as hyperspectral or infrared cameras, which may increase system complexity and cost [5–7]. These requirements may limit their application in small laboratories or cost-constrained industrial settings.

Several studies have also used multimodal or composite freshness indicators based on simple geometric and physical measurements. Harnsoongnoen and Jaroensuk [4] proposed a machine vision system for measuring egg dimensions together with a weighing sensor for determining egg mass, which enabled egg density estimation and freshness assessment. Similarly, weight loss and storage temperature have been used as input variables in deep learning models to predict Haugh unit values, demonstrating the usefulness of combining correlated freshness-related indicators [10]. These studies suggest that integrating geometric information, such as air-cell size, with weight-related parameters can provide a more robust assessment than single-parameter approaches, particularly when relatively accessible sensing methods are used [4],[10].

Despite these developments, the systematic combination of image-based air-cell measurement and weight-loss analysis for monitoring egg freshness-related changes using low-cost hardware remains limited. Earlier multimodal systems have commonly used shell-based geometric characteristics and weight for egg grading [4],[12], whereas more advanced approaches often rely on specialized imaging modalities, such as hyperspectral or thermal cameras [5],[8]. Although conventional imaging and weight measurement are more accessible, their combined use for monitoring air-cell development and cumulative weight loss has not been sufficiently clarified, particularly when evaluated repeatedly on the same egg samples during storage. To address this gap, the present study focuses on a practical laboratory-scale approach that combines two measurable freshness-related indicators: egg weight loss and image-derived

air-cell area. Instead of proposing a fully automatic classification system, this work develops and evaluates a GUI-based semi-automated measurement workflow using readily available hardware, including a USB camera, controlled illumination, and a precision weighing system. The framework allows quantitative monitoring of physical and structural changes in eggs during storage while preserving sample integrity. This approach provides baseline evidence for future development of automatic air-cell segmentation, validated freshness classification models, and scalable egg quality monitoring systems.

3. Materials and Methods

3.1 Egg Sample and Experimental Design

Measurements were performed at five predefined storage time points to capture progressive changes in egg mass and air-cell enlargement during storage. Day 1 served as the baseline, at which the initial egg weight and air-cell size were recorded immediately after sample collection. Subsequent measurements were conducted on Day 6 and Day 11 to represent the mid-storage period, and on Day 16 and Day 21 to characterize extended storage conditions.

At each time point, the same 100 eggs were subjected to weight measurement and image acquisition for air-cell analysis. Each measurement session was completed within a four-hour window to minimize the influence of ambient temperature fluctuations and ensure consistency across samples. This repeated-measurement design allowed changes in egg weight and air-cell size to be tracked over time for each individual egg.

A total of 100 eggs were obtained from the same commercial batch to reduce variation caused by differences in production source, handling history, and storage background. This sample size was selected to provide sufficient sample coverage for observing freshness-related changes over the storage period while maintaining practical feasibility for repeated image acquisition and weighing. Eggs with visible shell cracks, shell damage, severe surface contamination, abnormal shape, or unclear identification were excluded. Only intact eggs with normal external appearance were included in the experiment.

3.2 Weight Measurement System

Egg weight was measured using a high-precision analytical balance (Luna Analytical Balances, LAB 214i) with a readability of 0.0001 g and a maximum capacity of 220 g. The balance was calibrated daily using certified calibration weights before each measurement session to ensure accuracy. Eggs were allowed to equilibrate to room temperature for 30 min prior to weighing to minimize thermal effects on measurement accuracy. The recorded weight values were used to calculate egg weight loss over the storage period.

Each egg was carefully placed in the center of the weighing pan, and the weight was recorded once the

display stabilized, typically within 3–5 s, as shown in **Figure 1**. Three consecutive measurements were taken for each egg, and the average value was calculated to minimize random error. Weight loss percentage was calculated using Eq. (1):

$$\text{Weight Loss (\%)} = \frac{W_0 - W_t}{W_0} \times 100 \quad (1)$$

where W_0 represents the initial weight at Day 1, and W_t represents the weight at time t .



Figure 1 Egg weight measurement using the Luna Analytical Balance LAB 214i.

3.3 Image Acquisition System

A custom imaging system was designed and constructed specifically for air-cell visualization and measurement, as shown in **Figure 2(a)**. The system consisted of the following components:

- **Camera:** 4-megapixel USB camera (SMTKEY) operating at 30 frames per second and equipped with a 5–50 mm varifocal lens.
- **Illumination:** Two red LED light sources with a wavelength range of 620–625 nm and a power rating of 3 W each, positioned at 45° angles beneath the egg sample.
- **Egg holder:** A custom 3D-printed egg holder with a transparent base to allow light transmission while securing the egg in a consistent position.
- **Enclosure:** A light-tight chamber with dimensions of 40 cm × 40 cm × 40 cm to eliminate ambient light interference.
- **Positioning system:** An adjustable camera mount used to maintain a fixed distance of 30 cm between the camera lens and the egg apex.

Red LED illumination was selected based on preliminary tests showing improved contrast between the air cell and the surrounding egg contents at this wavelength range. The backlighting configuration enabled the air cell to be visualized as a darker region against the illuminated egg contents, as shown in **Figure 2(b)**.

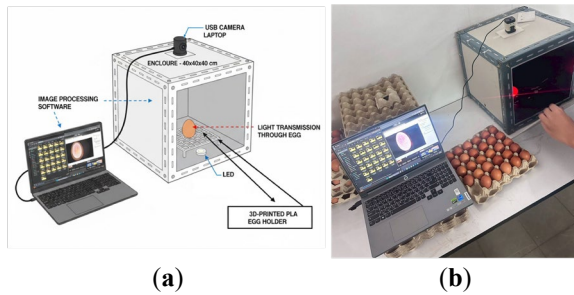


Figure 2 Custom imaging system: (a) conceptual overview and (b) real prototype during operation.

3.4 GUI-Based Semi-Automated Image Measurement Tool

Image analysis was performed using custom software developed in Python 3.11 with the OpenCV library. The software was designed as a GUI-based semi-automated measurement tool to support egg boundary detection and air-cell area analysis. The workflow of the developed tool is shown in **Figure 3**, and examples of the raw and processed images are shown in **Figure 4**.

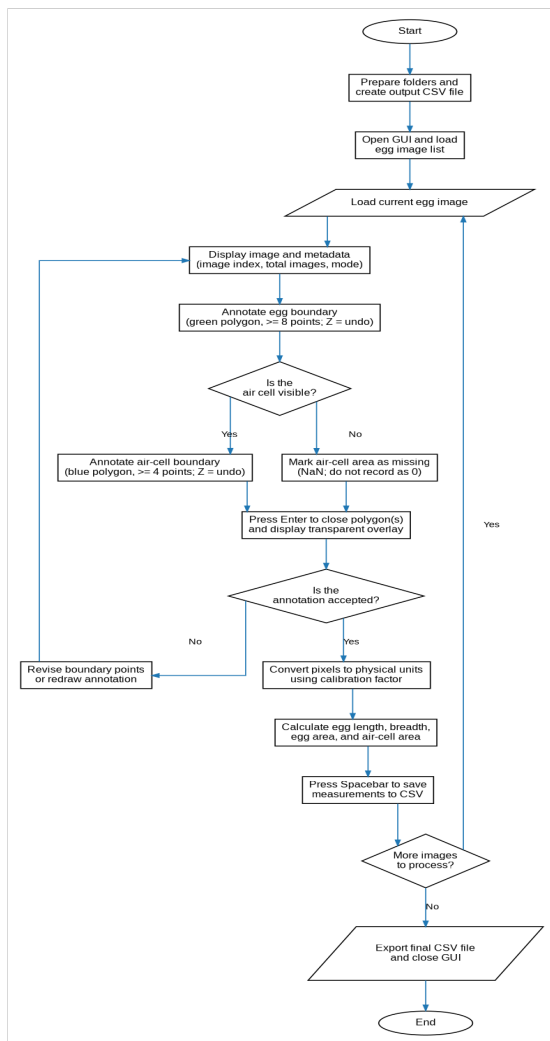


Figure 3 Image processing flowchart.

The image acquisition process produced RGB images of individual eggs under controlled illumination. **Figure 4(a)** shows an example of the original RGB candling image used as the input image. The image was loaded into the OpenCV-based graphical user interface, where the user manually selected boundary points for the whole egg and the visible air-cell region. The whole egg boundary was marked using a polygon surrounding the outer egg contour, whereas the air-cell region was marked using a separate polygon around the visible air-cell area. If the air cell was not clearly visible, the annotation was skipped and recorded as missing data rather than as a zero value. After all boundary points were selected, the program automatically connected the coordinate points to form closed polygonal contours. Binary masks were then generated for the whole egg and air-cell regions. A semi-transparent overlay was applied to the original image to visualize the selected regions, as shown in **Figure 4(b)**. This overlay allowed the user to verify whether the selected boundaries correctly represented the egg and air-cell regions before saving the measurement results.

The program fitted an ellipse to the user-defined whole egg contour to estimate the major and minor axes of the egg. The major axis represented egg length, whereas the minor axis represented egg breadth. Pixel-based measurements were converted into millimeters using a calibration factor of 0.175 mm/pixel. This calibration factor was obtained by photographing a Thai 1-baht coin of known diameter under the same imaging conditions as the egg samples. The same calibration factor was then applied to convert image-derived length, breadth, egg area, and air-cell area into metric units. The air-cell area ratio was calculated as the percentage of air-cell area relative to the whole egg area. All computed values were displayed on the screen and exported to a CSV file for statistical analysis.

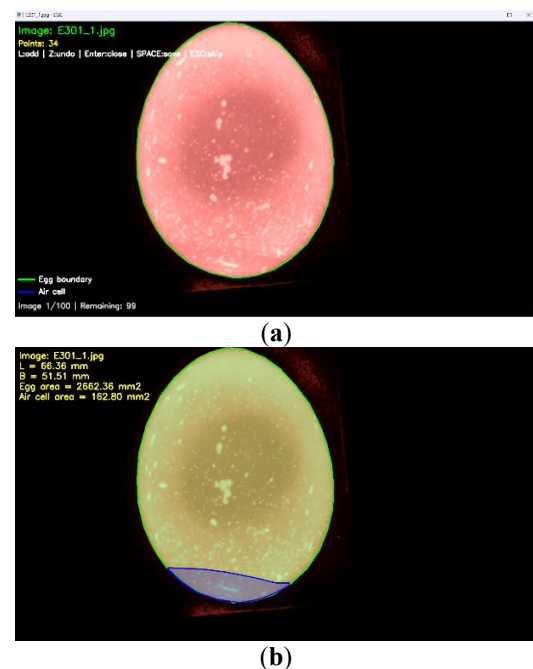


Figure 4 Example of image analysis: (a) raw egg image and (b) processed image after air cell area measurement.

3.5 Validation of Image-Derived Measurements

To evaluate the reliability of the GUI-based image measurement tool, GUI-derived egg dimensions were compared with manually measured reference values. A total of 100 eggs were independently measured using Vernier calipers to obtain reference values for egg length and breadth. The same egg images were then analyzed using the developed GUI-based measurement program, and the program-derived length and breadth values were compared with the manual measurements. The percentage error was calculated using Eq. (2):

$$Error(\%) = \left| \frac{V_{GUI} - V_{ref}}{V_{ref}} \right| \times 100 \quad (2)$$

where V_{GUI} represents the value obtained from the GUI-based image measurement program, and V_{ref} represents the reference value measured using Vernier calipers.

3.6 Data Analysis

Statistical analyses were performed using Python 3.11 with the SciPy and Statsmodels libraries on macOS. Descriptive statistics, including mean, standard deviation, minimum, and maximum values, were calculated for egg weight, cumulative weight loss percentage, and air-cell area at each storage time point. Skipped or non-visible air-cell annotations were treated as missing values rather than numerical zeros and were excluded from air-cell area calculations. The number of valid and missing observations was reported for each storage day.

Cumulative weight loss percentage was calculated relative to the initial egg weight on Day 1. Linear regression analysis was performed using individual egg-level raw data rather than averaged values to preserve natural variation and avoid overestimation of R^2 . Regression analysis was used to evaluate the relationship between cumulative weight loss and air-cell area or air-cell area ratio. Because the same eggs were measured repeatedly at five storage time points, repeated-measures ANOVA was used to evaluate the effect of storage duration on egg weight, cumulative weight loss percentage, and air-cell area. In this analysis, storage time was treated as the within-subject factor, and egg ID was treated as the subject factor. The repeated-measures model can be expressed as Eq. (3):

$$Y_{ij} = \mu + T_j + S_i + \varepsilon_{ij} \quad (3)$$

where Y_{ij} represents the measured response of egg i at storage time j , μ is the overall mean, T_j is the effect of storage time, S_i is the subject effect of each egg, and ε_{ij} is the residual error. This model accounts for the correlation among repeated observations taken from the same egg. When a significant storage-time effect was detected, Bonferroni-adjusted post hoc comparisons were performed to identify differences

among storage days. Results were reported as F-statistics with degrees of freedom, p-values, and partial eta squared (η^2p) as an effect size.

4. Results and Discussion

4.1 Weight Loss Progression

Table 1 and Figures 5(a) and 5(c) summarize the descriptive statistics of egg weight and cumulative weight loss across the five storage time points. The same 100 eggs were repeatedly measured from Day 1 to Day 21 to monitor progressive changes in egg mass during storage.

Table 1 Egg weight measurements and cumulative weight loss during storage period (n=100)

Day	Mean Weight (g)	SD (g)	Cumulative weight Loss (%)
Day 1 (Baseline)	59.448	4.0826	0.0000
Day 6	58.7405	4.0612	1.1931
Day 11	58.0597	4.0350	2.3403
Day 16	57.4573	4.0049	3.3540
Day 21	56.9427	3.9963	4.2220

At baseline, the mean egg weight was 59.4480 g with a standard deviation of 4.0826 g. A consistent reduction in mean egg weight was observed throughout the 21-day storage period, decreasing from 59.4480 g on Day 1 to 56.9427 g on Day 21. This trend indicates continuous mass loss during storage, which is commonly associated with moisture loss through the eggshell. Cumulative weight loss increased progressively with storage time, from 1.1931% on Day 6 to 2.3403% on Day 11, 3.3540% on Day 16, and 4.2220% on Day 21. The steady increase in weight loss suggests a gradual dehydration process during storage. These findings support the use of egg weight loss as a quantitative indicator of freshness deterioration. Repeated-measures ANOVA was used to evaluate the effect of storage duration on egg weight because the same 100 eggs were measured repeatedly across five time points. The analysis showed a significant effect of storage duration on egg weight, $F(4, 396) = 3466.98$, $p < 0.001$, $\eta^2p = 0.972$. This result indicates that egg weight changed significantly during storage. Bonferroni-adjusted post hoc comparisons confirmed significant differences among storage days, supporting the progressive reduction in egg weight over the 21-day storage period.

Linear regression analysis was performed using individual egg-level raw data points rather than mean values at each storage time point. The relationship between storage duration and cumulative weight loss percentage was modeled to describe the progression of weight loss over time while preserving the natural variability among individual eggs. The regression equation was Eq. (4):

$$\text{Weight Loss (\%)} = 0.212 \times \text{Days} - 0.111 \quad (4)$$

The coefficient of determination ($R^2 = 0.919$) indicated the degree to which storage duration explained variation in cumulative weight loss among individual egg-level observations.

4.2 Air-Cell Expansion Analysis

Air-cell area measurements showed a progressive increase throughout the storage period, as summarized in **Table 2** and illustrated in **Figures 5(b)–(d)**. In this analysis, skipped or non-visible air-cell annotations were treated as missing data rather than numerical zero values. Therefore, only valid air-cell measurements were included in the calculation of descriptive statistics to avoid distortion of the mean, standard deviation, minimum, and maximum values.

Table 2 Air-cell area measurements during storage

Day	Mean Area (mm ²)	SD (mm ²)	Min (mm ²)	Max (mm ²)
Day 1 (Baseline)	90.6	53.9	15.9	311.28
Day 6	128.6	64.2	40.3	523.86
Day 11	187.7	84.9	75.4	581.82
Day 16	226.2	93.8	97.5	509.00
Day 21	274.7	106.3	118.3	613.00

Note: Values were calculated using valid air-cell observations only. Skipped or non-visible air-cell annotations were treated as missing data rather than numerical zero values. The experiment included 100 eggs measured across five storage time points.

The mean air-cell area increased progressively from 90.6 mm² on Day 1 to 274.7 mm² on Day 21, indicating continuous air-cell enlargement during storage. This trend is consistent with moisture loss and gas exchange through the eggshell, which are known to occur as eggs age. Repeated-measures ANOVA was performed using complete cases with valid air-cell measurements across all five storage time points. The analysis showed a significant effect of storage duration on air-cell area, $F(4, 300) = 111.09$, $p < 0.001$, $\eta^2p = 0.597$. This result confirms that air-cell area increased significantly during storage.

Linear regression analysis using individual valid air-cell observations produced Eq. (5):

$$\text{Air-cell area (mm}^2\text{)} = 9.338 \times \text{storage time} + 78.731 \quad (5)$$

The regression model showed a positive relationship between storage time and air-cell area, with $R^2 = 0.370$.

Substantial variability in air-cell area was observed among individual eggs, as indicated by the standard deviations and the spread of individual data points in **Figure 5(d)**. This variability may reflect differences in shell porosity, shell structure, and moisture transfer rates among eggs. These findings support the use of air-cell enlargement as a measurable indicator of freshness deterioration during storage.

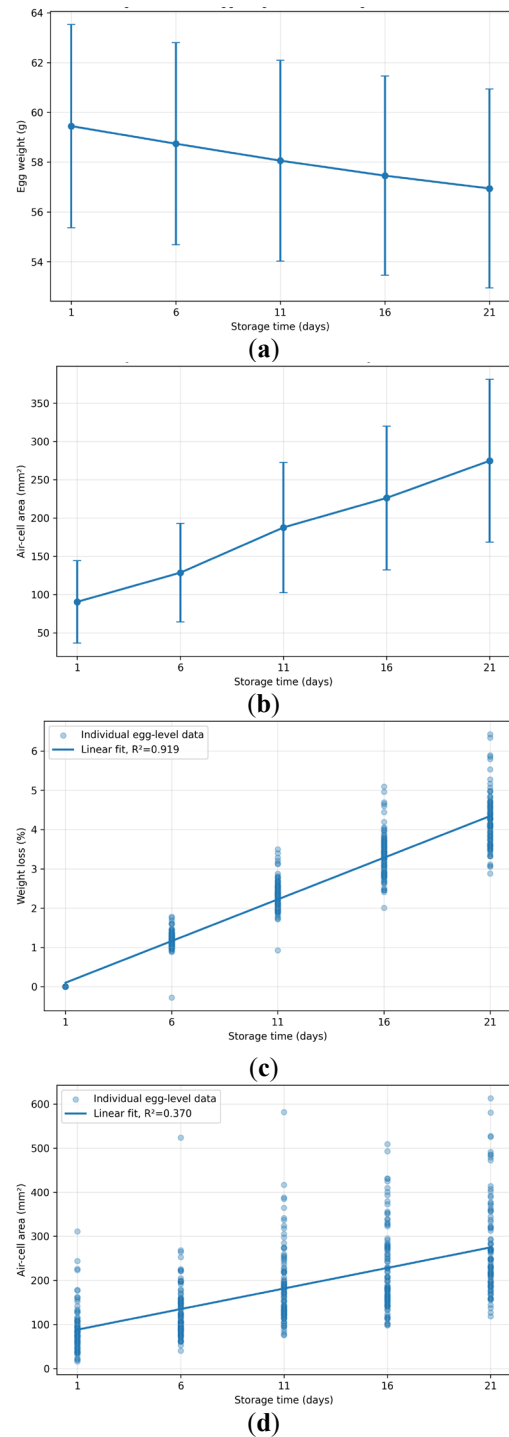


Figure 5 Changes in egg weight loss and air-cell area during storage: (a) mean egg weight across storage time points, (b) mean air-cell area across storage time points, (c) individual egg-level relationship between storage time and weight loss percentage, and (d) individual egg-level relationship between storage time and air-cell area.

4.3 Validation of GUI-Based Image Measurement

The consistency of the GUI-based image measurement tool was evaluated by comparing GUI-derived egg dimensions with manually measured reference values obtained using Vernier calipers. The comparison focused on egg length and breadth because these two parameters were directly measured by both

methods. The percentage error was calculated to determine the difference between the GUI-derived measurements and the manual reference measurements.

Table 3 Percentage error between GUI-derived and manually measured egg dimensions

Day	Length Error (%)	Breadth Error (%)
Day 1	16.69 ± 0.02	16.65 ± 0.02
Day 6	16.73 ± 0.02	17.00 ± 0.02
Day 11	16.78 ± 0.02	16.73 ± 0.02
Day 16	16.52 ± 0.03	16.47 ± 0.02
Day 21	17.57 ± 0.09	17.21 ± 0.08

As shown in **Table 3**, the mean percentage error for egg length ranged from 16.52% to 17.57%, whereas the mean percentage error for egg breadth ranged from 16.47% to 17.21% across the storage period. The error values were relatively consistent from Day 1 to Day 16, indicating stable measurement behavior of the GUI-based tool under the experimental imaging setup. A slightly higher error was observed on Day 21, particularly for egg length, which may be related to differences in egg orientation, camera perspective, or boundary selection during image acquisition and annotation.

Although the GUI-derived measurements showed systematic differences from the Vernier caliper measurements, the consistency of the error values suggests that the developed tool can be used for relative monitoring of morphological changes and air-cell development during storage. Therefore, the current GUI-based tool should be interpreted as a relative monitoring tool and as a supporting method for air-cell area ratio analysis rather than as a fully validated method for highly accurate absolute dimensional measurement. Future improvements in calibration, fixed egg positioning, camera alignment, and automatic boundary detection are required to improve absolute measurement accuracy.

4.4 Correlation Between Weight Loss and Air-Cell Area

Eggs were stratified by initial weight into four size classes: Small (S, 45.01–53.00 g), Medium (M, 53.01–63.00 g), Large (L, 63.01–73.00 g), and Extra-Large (XL, >73.01 g). This size-based grouping was used because egg size may influence moisture loss and air-cell development through differences in surface-area-to-volume ratio, shell characteristics, and internal egg volume. Therefore, analyzing the relationship between cumulative weight loss and air-cell expansion by size group provides a clearer understanding of how egg size affects freshness-related changes during storage.

Figure 6 shows the relationship between cumulative weight loss (%) and air-cell area ratio (%) using individual egg-level raw data. A total of 100 eggs were measured at five storage time points, resulting in a maximum of 500 possible observations. After excluding skipped or non-visible air-cell measurements, 469 valid observations were included

in the regression analysis. These consisted of 22 observations from the small egg group, 369 observations from the medium egg group, 72 observations from the large egg group, and 6 observations from the extra-large egg group. Each point in **Figure 6** represents one egg measurement at one storage time point.

The overall model produced $R^2 = 0.417$, $p < 0.001$, indicating that approximately 41.7% of the variation in air-cell area ratio could be explained by cumulative weight loss. This result confirms that eggs with greater weight loss tended to exhibit larger air-cell area ratios during storage. However, the moderate R^2 value also indicates that air-cell expansion is not determined by weight loss alone and that other egg-specific factors may contribute to the observed variation.

When analyzed separately by egg-size group, positive relationships were observed for small, medium, and large eggs. The small egg group showed the highest coefficient of determination ($R^2 = 0.567$, $p < 0.001$), followed by the medium group ($R^2 = 0.438$, $p < 0.001$) and the large group ($R^2 = 0.421$, $p < 0.001$). These results suggest that cumulative weight loss was moderately associated with air-cell expansion across these size groups. In contrast, the extra-large group showed a weak and non-significant relationship ($R^2 = 0.178$, $p = 0.404$), which may be explained by the small number of valid observations in this group.

Compared with regression analysis based on averaged values, analysis using individual raw data produced lower but more realistic R^2 values. This approach better represents the natural biological variability among individual eggs. The results indicate that weight loss is an important contributor to air-cell enlargement during storage, but the relationship is influenced by egg-to-egg variation, including shell porosity, shell thickness, initial egg structure, and size-related differences. Therefore, both cumulative weight loss and air-cell characteristics should be considered together when assessing freshness-related changes in eggs during storage.

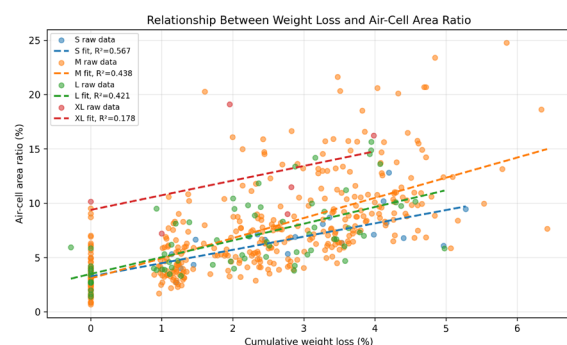


Figure 6 Relationship between cumulative weight loss (%) and air-cell area ratio (%) using individual egg-level raw data.

4.5 Implications for Egg Freshness Assessment

The findings of this study provide important insights into non-destructive egg freshness assessment

during storage. Progressive weight loss and air-cell enlargement were observed throughout the storage period, reflecting moisture loss and internal structural changes that occur as eggs age. Although both parameters showed clear storage-related trends, their relationship varied among individual eggs and egg size classes. This variation indicates that relying on a single indicator may not fully capture the complexity of freshness deterioration.

Weight-based measurement provides a simple and practical indicator of mass loss, whereas image-derived air-cell measurement provides direct structural information related to internal egg aging. When combined, these two indicators offer complementary information that can improve the robustness of freshness assessment. The integration of mass-based and image-derived features also allows cross-checking between external physical changes and internal structural changes, thereby reducing uncertainty associated with individual egg variability.

From a practical perspective, the results support the development of multi-parameter egg freshness assessment tools that integrate digital weighing and air-cell imaging. The proposed GUI-based semi-automated framework provides a practical approach for laboratory-scale freshness monitoring using low-cost hardware. However, further development is required before implementation in continuous industrial quality monitoring, particularly in terms of automatic segmentation, image acquisition speed, illumination control, and integration with conveyor-based handling systems. Overall, the findings emphasize that egg freshness assessment can benefit from combining physical and structural indicators rather than relying on a single measurement.

5. Conclusion

This study demonstrated the potential of combining non-destructive measurements of egg weight loss and image-derived air-cell enlargement for monitoring egg freshness-related changes during storage. The proposed approach preserved sample integrity by avoiding destructive testing and provided quantitative information on both physical mass loss and internal structural changes. By integrating these two indicators within a GUI-based semi-automated framework, the study provides a practical basis for laboratory-scale freshness assessment and future development toward industrial monitoring applications.

5.1 Key Findings

Egg weight decreased progressively throughout the storage period, with cumulative weight loss reaching approximately 4.22% after 21 days of storage. This trend indicates continuous moisture loss through the eggshell during storage. In parallel, air-cell area increased over time, reflecting internal structural changes associated with egg aging. Skipped or non-visible air-cell annotations were treated as missing data rather than numerical zero values to avoid distortion of descriptive statistics.

The relationship between cumulative weight loss and air-cell enlargement was evaluated using individual egg-level data. Overall, a positive association was observed, indicating that eggs with greater moisture loss tended to show larger air-cell areas. However, variability among individual eggs and egg size classes was also observed, suggesting that freshness assessment should not rely on a single indicator alone. These findings support the combined use of weight-based and image-derived features as complementary indicators for non-destructive monitoring of egg freshness-related changes.

5.2 Practical Significance

The results of this research have practical implications for non-destructive egg quality assessment. Conventional freshness evaluation methods often rely on destructive tests, such as breaking eggs to measure albumen height or calculate the Haugh unit. In contrast, the proposed method enables repeated monitoring of the same egg samples using digital weighing and image-based air-cell measurement.

This GUI-based semi-automated approach may be useful for laboratory-scale freshness monitoring and quality control studies where sample preservation is important. The combination of air-cell imaging and weight-loss measurement provides complementary information and may improve freshness evaluation compared with weight-only assessment. The framework may also provide a foundation for future smart egg inspection or IoT-based quality monitoring systems after further development of automatic segmentation, faster image acquisition, and industrial integration.

5.3 Limitations and Future Directions

Despite its strengths, this study has several limitations. First, the current system was evaluated under a single set of storage conditions, and environmental factors such as temperature and relative humidity were not varied. These factors are known to influence moisture loss and gas exchange and may affect the generalizability of the findings. Second, the current image measurement process required user-assisted polygon annotation of the egg and air-cell boundaries; therefore, the system should be considered a GUI-based semi-automated measurement tool rather than a fully automated inspection system. This manual annotation step may introduce operator-dependent variation and limit direct application in high-throughput industrial operations. In addition, the validation results showed systematic differences between GUI-derived egg dimensions and Vernier caliper measurements. Therefore, the current GUI-based measurement tool is more suitable for relative monitoring of morphological changes and air-cell area ratio analysis than for highly accurate absolute dimensional measurement. Future improvements in pixel-to-millimeter calibration, fixed egg positioning, camera alignment, and automatic boundary detection are required to improve absolute measurement accuracy.

Another practical limitation is that the imaging setup required a light-tight chamber and controlled bottom-up red LED illumination for each egg. These requirements may limit direct application in

continuous industrial operations without further system redesign. Future research should focus on replacing manual polygon annotation with automatic air-cell segmentation using computer vision or deep learning-based image segmentation techniques. Improved illumination design will also be necessary to enhance the contrast between the air cell and surrounding egg contents under different shell colors and egg orientations. In addition, conveyor-based image acquisition should be developed to allow continuous inspection of multiple eggs under controlled lighting conditions.

Further validation under different storage temperatures, humidity levels, egg sizes, and production batches is required to evaluate the robustness of the proposed framework. Additional non-destructive indicators, such as shell conductance, spectral features, or other imaging-based parameters, may also be integrated to improve freshness estimation and classification performance. Ultimately, pilot-scale and industrial-scale validation will be necessary to establish the applicability of the proposed framework for large-scale egg freshness assessment.

6. Acknowledgments

The authors gratefully acknowledge the Faculty of Engineering and Agro-Industry, Maejo University, for providing the venue and research facilities for this study. The authors also thank Charoen Pokphand Foods Public Company Limited (CPF) for supporting the project by providing eggs free of charge for research purposes.

7. References

- [1] Z. Gao, J. Zheng, and G. Xu, "Research Progress and Technological Application Prospects of Comprehensive Evaluation Methods for Egg Freshness," *Foods*, vol. 14, no. 9, 2025, Art. no. 1507, doi: 10.3390/foods14091507.
- [2] K. Drabik, T. Próchniak, K. Kasperek, and J. Batkowska, "The Use of the Dynamics of Changes in Table Eggs during Storage to Predict the Age of Eggs Based on Selected Quality Traits," *Animals*, vol. 11, no. 11, 2021, Art. no. 3192, doi: 10.3390/ani11113192.
- [3] H. E. Samli, A. Agha, and N. Senkoylu, "Effects of Storage Time and Temperature on Egg Quality in Old Laying Hens," *Journal of Applied Poultry Research*, vol. 14, no. 3, pp. 548–553, 2005, doi: 10.1093/japr/14.3.548.
- [4] S. Harnsoongnoen and N. Jaroensuk, "The grades and freshness assessment of eggs based on density detection using machine vision and weighing sensor," *Scientific Reports*, vol. 11, no. 1, 2021, Art. no. 16640, doi: 10.1038/s41598-021-96140-x.
- [5] K. Yao, J. Sun, L. Zhang, X. Zhou, Y. Tian, N. Tang, and X. Wu, "Nondestructive detection for egg freshness based on hyperspectral imaging technology combined with harris hawks optimization support vector regression," *Journal of Food Safety*, vol. 41, no. 3, 2021, Art. no. e12888, doi: 10.1111/jfs.12888.
- [6] P. Ong, S. -Y. Chiu, I. -L. Tsai, Y. -C. Kuan, Y. -J. Wang, and Y. -K. Chuang, "Nondestructive egg freshness assessment using hyperspectral imaging and deep learning with distance correlation wavelength selection," *Current Research in Food Science*, vol. 11, 2025, Art. no. 101133, doi: 10.1016/j.crfs.2025.101133.
- [7] E. Loffredi, S. Grassi, and C. Alamprese, "Spectroscopic approaches for non-destructive shell egg quality and freshness evaluation: Opportunities and challenges," *Food Control*, vol. 129, 2021, Art. no. 108255, doi: 10.1016/j.foodcont.2021.108255.
- [8] V. M. Nakaguchi and T. Ahamed, "Fast and Non-Destructive Quail Egg Freshness Assessment Using a Thermal Camera and Deep Learning-Based Air Cell Detection Algorithms for the Revalidation of the Expiration Date of Eggs," *Sensors*, vol. 22, no. 20, 2022, Art. no. 7703, doi: 10.3390/s22207703.
- [9] Q. Wang, X. Deng, Y. Ren, Y. Ding, L. Xiong, Z. Ping, Y. Wen, and S. Wang, "Egg freshness detection based on digital image technology," *Scientific Research and Essay*, vol. 4, no. 10, pp. 1073–1079, 2009.
- [10] T. H. Kim, J. H. Kim, J. Y. Kim, and S. E. Oh, "Egg Freshness Prediction Model Using Real-Time Cold Chain Storage Condition Based on Transfer Learning," *Foods*, vol. 11, no. 19, 2022, Art. no. 3082, doi: 10.3390/foods11193082.
- [11] J. Hansot, W. Wongsaroj, T. Sangsuwan, and N. Thong-un, "A low-cost autonomous portable poultry egg freshness machine using majority voting-based ensemble machine learning classifiers," *Smart Agricultural Technology*, vol. 10, 2025, Art. no. 100768, doi: 10.1016/j.atech.2025.100768.
- [12] X. Yang, R. B. Bist, S. Subedi, and L. Chai, "A Computer Vision-Based Automatic System for Egg Grading and Defect Detection," *Animals*, vol. 13, no. 14, 2023, Art. no. 2354, doi: 10.3390/ani13142354.
- [13] J. Pardede, M. F. Z. A. Rawosi, A. P. Setyaningrum, R. M. Milenio, and C. Chazar, "Egg Weight Estimation Based on Image Processing using Mask R-CNN and XGBoost," *Journal of Applied Data Sciences*, vol. 6, no. 4, pp. 3005–3016, 2025, doi: 10.47738/jads.v6i4.1004.
- [14] C. Quan, Q. Xi, X. Shi, R. Han, Q. Du, F. Forghani, C. Xue, J. Zhang, and J. Wang, "Development of predictive models for egg freshness and shelf-life under different storage temperatures," *Food Quality and Safety*, vol. 5, 2021, Art. no. fyab021, doi: 10.1093/fqsafe/fyab021.
- [15] J. S. Garcia, R. K. Gast, Q. D. Read, and D. R. Jones, "The impact of egg handling and storage temperature on shell eggs stored for 27 weeks: Egg quality," *Poultry Science*, vol. 105, no. 2, 2025, Art. no. 106264, doi: 10.1016/j.psj.2025.106264.