



Monitoring postharvest water loss in eggplants (*Solanum melongena* L.) using UV-induced fluorescence imaging and multivariate analysis

Vincent Rotich^{a,d}, Tianqi Gao^a, Panintorn Premprea^a, Takahiro Hayashi^a, Kazuhiko Namba^{b,*}, Mitsuji Monta^b, Motomi Nishimoto^c, Naoshi Kondo^a

^a Laboratory of Biosensing Engineering, Graduate School of Agriculture, Kyoto University, Kitashirakawa, Kyoto, 606-8267, Japan

^b Faculty of Environmental, Life, Natural Science and Technology, Okayama University, Okayama, 700-8530, Japan

^c Technology and Innovation Center, Daikin Industries, Ltd., 1-1, Nishi-Hitotsuya, Settsu, Osaka, 566-8585, Japan

^d Omi Weighing Machine Inc., Kusatsu, Shiga, 525-0054, Japan

ARTICLE INFO

Keywords:

Eggplant
Fluorescence spectroscopy
UV-Induced imaging
Water loss
Postharvest quality
Non-destructive assessment

ABSTRACT

Eggplant (*Solanum melongena* L.) is susceptible to significant postharvest losses primarily due to water loss during storage, which affects market quality by causing texture and glossiness degradation. We investigated whether UV-induced fluorescence imaging and EEM (Excitation-Emission Matrix) fluorescence spectroscopy can non-destructively monitor WL under four storage regimes (10 °C/95 % RH, 20 °C/95 % RH, 20 °C/75 % RH, 10 °C/75 % RH). EEMs exhibited three regions; a 365/420 nm blue emission increased most under warm, low-humidity storage and is consistent with phenolic/lignin-related fluorescence. Side-view fluorescence (FL) images showed progressive blue-white emission and surface textural changes that tracked gravimetric water loss (WL). A PLSR model using combined color and texture features from FL and reflectance (CL) images achieved $R^2_{CV} = 0.88$ (RMSECV = 3.47 %) with only six features. To test a minimal predictor, we fit an Analysis of Covariance (ANCOVA) using Day-1 FL MeanBlue as a covariate and storage category as a factor with Leave One Out Cross-validation (LOOCV); this forecasted cumulative WL with $R^2_{LOOCV} = 0.92$ and MAE = 1.88 %. Importantly, this ANCOVA model using Day-1 blue-band fluorescence as a covariate was predictive only under 20 °C/75 % RH; under the other conditions, its contribution was weak. Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) models achieved accuracies of 94.4 % and 85.2 %, respectively, in differentiating storage conditions. These results support low-cost FL imaging as a practical tool to monitor WL and storage stress.

1. Introduction

Eggplant (*Solanum melongena* L.), indigenous to tropical and subtropical regions of Asia, is widely cultivated worldwide for its desirable nutritional profile. While eggplants can be stored for extended periods, especially with modified and controlled atmosphere storage, they remain susceptible to postharvest losses like many other perishable vegetables. This vulnerability is particularly pronounced due to extensive global distribution and transport chains. Research indicates that 45–55 % of food loss occurs during the postharvest handling and storage stages of the supply chain (Xue et al., 2021). A significant portion of these losses is attributed to water loss through transpiration. Even a modest 5 % fresh weight loss in perishable commodities results in a noticeable decline in freshness and marketability (Mahajan et al., 2008). This water loss is driven by the water vapor pressure deficit between the fruit and

its environment, leading to changes in osmotic pressure (Ben-Yehoshua & Rodov, 2002; Gidado et al., 2024). As a result, the decrease in peel turgor pressure leads to undesirable textural changes and a decrease in peel gloss, which affects the market value and consumer acceptance (Díaz-Pérez, 1998).

Several conditions, including temperature and humidity, affect the rate of water loss in stored eggplant to a great extent. Studies have shown that high temperatures accelerate water loss by increasing transpiration rates. Low temperatures slow metabolic processes and reduce water loss, but they also pose a risk of chilling injury (Pauli, 1999). In low humidity conditions, water loss through the skin occurs rapidly; hence, dehydration occurs at a high rate, while in high humidity conditions, water loss is low. Nevertheless, very high humidity leads to mold growth and other pathogenic activities. These are the interactions that take place, and therefore, the storage conditions must be optimal, a task

* Corresponding author.

E-mail addresses: rotich.vincent@omiscale.co.jp (V. Rotich), kaz@okayama-u.ac.jp (K. Namba).

<https://doi.org/10.1016/j.foodcont.2025.111902>

Received 3 September 2025; Received in revised form 7 November 2025; Accepted 7 December 2025

Available online 8 December 2025

0956-7135/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

that is not easy to achieve (Gidado et al., 2024). The storage of eggplants is, therefore, undesirable under certain abiotic factors, and early detection of the effects of these factors is essential to reducing post-harvest losses.

The effect of water loss during storage can be monitored using both external and internal quality evaluation techniques. Sensory evaluation is a common technique used to assess organoleptic properties (Gajewski & Arasimowicz, 2004). In their study (Jha et al., 2002), evaluated data including weight, surface stiffness, and surface gloss indicators in eggplants during storage. Imaging and spectroscopy-based optical approaches have been used to assess eggplant quality. Commonly employed techniques include NIR spectroscopy (Jha et al., 2002), chlorophyll fluorescence (Calvo et al., 2017), and hyperspectral imaging (Tsouvaltzis et al., 2020). These approaches offer non-destructive techniques for evaluating quality indicators associated with water loss in eggplants during storage.

Several studies have confirmed that fluorescence intensity increases with water loss progression in perishable commodities. Additionally (Wright et al., 2009), investigated the dependence of chlorophyll *a* fluorescence on water status in grapes and determined that fluorescence variables correlated with mass loss during dehydration. Also (Nurulhuda et al., 2021), measured the fluorescence characteristics on tomato surfaces during the over-ripening stage, where fluorescence intensity correlated with weight loss. Through fluorescence imaging, they were able to classify fresh tomatoes and spoiled tomatoes accurately and showed that the method could be used to measure freshness and water loss. Moreover (Wulf et al., 2005), used laser-induced fluorescence spectroscopy (LIFS) on apples and carrots undergoing storage and attributed variation in fluorescence intensity to changes in fruit pigments due to variations caused by storage conditions. Overall, these studies show the capability of fluorescence techniques for monitoring water loss and quality assessment in perishable produce.

These approaches operate on the idea that when a substance is exposed to excitation light, it emits fluorescence at a longer wavelength (Albrecht, 2008). Eggplants are ideal candidates for these approaches owing to their high phytochemical content. They have numerous biologically active compounds, such as antioxidant phenolic acids and flavonoids in the pulp, and anthocyanins (primarily Nasunin) in the skin (Condurache et al., 2021; Gürbüz et al., 2018; Stommel & Whitaker, 2003). It also contains essential amino acids, including leucine, valine, lysine, and isoleucine (Padmanabhan et al., 2016). These compounds exhibit intrinsic fluorescence characteristics (Drabent et al., 1999; Monago-Maraña et al., 2016). EEM (Excitation-Emission Matrix) fluorescence spectroscopy provides a detailed spectral fingerprint of the fruit by capturing fluorescence at multiple excitation and emission wavelengths (Nurulhuda et al., 2021). Additionally, UV-induced fluorescence imaging helps detect changes not visible under normal lighting conditions (Al Riza et al., 2023; Konagaya et al., 2020).

Although reflectance-based optical techniques such as VIS-NIR spectroscopy and hyperspectral imaging have been used to evaluate the quality of eggplant (Babellahi et al., 2020; Tsouvaltzis et al., 2020), they measure bulk absorption and scattering properties, which target internal attributes but are less sensitive to surface alterations (Lu et al., 2020; Pandiselvam et al., 2022). They also need complicated pre-processing pipelines. In comparison, the UV-excited fluorescence mainly comes out of exocarp fluorophores since the UV-A is severely attenuated in the epidermis (Bilger et al., 2001). As a result, the emission observed is primarily due to near-surface layers and responsive to early cuticle changes (Konagaya et al., 2020; Momin et al., 2013).

In this research, we designed and implemented a low-cost imaging system to monitor the effects of postharvest environmental conditions in eggplants by examining their fluorescence properties and suitable excitation and emission wavelengths. The use of wavelength-specific LEDs and optical filters in the system would enable the monitoring of specific attributes of eggplants during the storage period. This research aims to characterize eggplants' fluorescence characteristics under

Table 1

Treatment conditions for each category.

Temperature (°C)	Relative Humidity (%)	No. of samples
10	75	14
10	95	14
20	75	14
20	95	14

different storage conditions using EEM fluorescence spectroscopy and to apply UV-induced fluorescence imaging to examine whether fluorescence images change depending on postharvest environmental conditions. To estimate the influence of storage environments on eggplant quality, we analyze the relationship between images of eggplant fluorescence and eggplant water loss.

In the experiment, fruits were stored at two different temperatures: 10 °C and 20 °C. For each temperature, two humidity levels were set: 75 % and 95 %. The EEM measurements, reflectance, and UV-induced fluorescence image data were then acquired. Weight loss was monitored by measuring the weight of each eggplant at regular intervals. To analyze the data collected, multivariate statistics were utilized to select and evaluate important features correlating fluorescence characteristics with water loss. This approach seeks to establish a non-destructive method for early detection of water loss in stored eggplants. To the best of our knowledge, no prior research has systematically characterized the fluorescence properties of eggplants during postharvest storage, making this study the first to provide such insights.

2. Materials and methods

2.1. Eggplant samples

Eggplants (*Solanum melongena* L.), cv. Senryo 2 (F1; Takii Seed Co.), graded as 'Kaku', which is the highest quality grade in the JA Binan, Okayama prefecture, Japan, was used in this study. These 'Kaku' eggplants are valued for their dark purple color, glossy skin surface, and characteristic purple calyx. This cultivar and grade were selected to ensure sample uniformity and consistency in physical characteristics, which is critical for establishing baseline fluorescence signatures and minimizing biological variability in this study.

They are cultivated in greenhouses from late September to June, with peak shipping between April and June. Due to the introduction of natural enemies of insects, such as thrips, the use of pesticides and frequency of spraying is minimal. Producers usually harvest eggplants 20–25 days after flowering. Harvesting is done in the morning and transported to the grading facility after pre-sorting on the farm.

The eggplant samples, freshly harvested in the morning and graded at the JA Binan grading facility, were packed in a box and transported to Kyoto University for measurement at room temperature. All samples were harvested at commercial maturity and graded within a 24-h period, ensuring uniform initial developmental stage. Initial fruit measurements showed length of 12–15 cm and weight ranging from 60.9 to 88.1 g (mean: 75.6 ± 6.3 g, $n = 56$), with the 56 defect-free samples exhibiting similar distributions. Initial weight, EEM fluorescence spectroscopy, color, and UV-fluorescence image measurements were conducted, and then the samples were divided into four categories. The samples were placed in 4 incubators (KMH-050, AS ONE Corporation, Japan) set at different temperatures and humidity, as shown in Table 1. These conditions were selected to separate the effects of temperature and humidity. 10 °C represents the recommended cold storage while 20 °C simulates ambient conditions (Gajewski et al., 2009). 95 % RH follows recommendations for limiting transpiration, while 75 % RH creates a higher vapor pressure deficit. Within each incubator, the ambient relative humidity was 75 %. For 95 % relative humidity, the eggplants in categories B and D were placed in a tightly sealed stainless-steel container. Each category chamber had temperature and humidity data

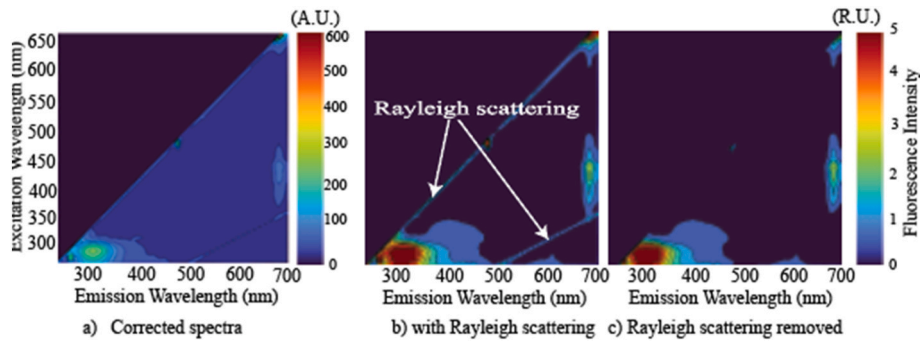


Fig. 1. EEM preprocessing; a) EEM after spectral correction, b) EEM converted to Raman Units (R.U.), c) EEM with Rayleigh scattering removed.

loggers (RSW-21S, ESPEC MIC, Japan). The samples' weight was measured at three-day intervals using an electronic balance with a readability of 0.01 g.

2.2. Excitation-Emission Matrix (EEM) measurement

A JASCO FP-8300 spectrofluorometer (Jasco Co., Japan) was used to acquire fluorescence EEM data using a front-face measurement setup with a sample holder (JASCO FDA-808 and FP-1061). For each category, one sample was randomly selected on the 1st, 7th, and 14th days for EEM measurement. Since sampling by EEM is destructive and spectrofluorometer measurements are time-consuming, only a single representative sample per type of storage was analyzed at a given time. Although this small sample size brings the possibility of variability, the EEM measurements were used mainly to determine key fluorescence regions and emission wavelengths, which could be studied non-destructively in all samples using the imaging system as described in Section 2.3. The measurement intervals (Days 1, 7, and 14) were selected to capture early, mid, and late storage fluorescence changes while balancing the destructive nature of sampling.

For each eggplant, a sample of 20 mm in diameter and 4 mm in thickness was obtained from the top, center, and bottom longitudinal regions of the fruit, sampled using a cylindrical punching tool. Samples included the peel and the immediate subjacent pericarp, which was then placed in the sample holder. Measurements were obtained at excitation wavelengths (260–650 nm) and emission wavelengths (270–700 nm), at 5000 nm/min scan speed, 50 ms response, low sensitivity, 5 nm bandwidth, and 5 nm data interval for both excitation and emission wavelengths. The EEM measurements were calibrated to account for light source variations and detector response variations; this calibration process utilized spectra obtained from a halogen light source and Rhodamine B as reference standards. Following the method described by (Tan et al., 2020), the Rayleigh scattering was removed from the EEM data using a bandwidth-masking approach, where intensity values

within a 25 nm range around the first-order and second-order scattering lines were set to zero, as shown in Fig. 1. The Raman peak intensity of distilled water was measured at a 350 nm excitation and integrated in the 371–428 nm range before the EEM measurement for calibrating Raman units. Water Raman calibration is necessary as it gives a solid point of reference to fluorescence measurements. This enables a direct comparison to be made between samples and time points by accounting for instrumental variations and standardizing intensity values. Following the procedure outlined by (Lawaetz & Stedmon, 2009), the EEM data were converted from Arbitrary units into Raman Units (R.U.) to standardize time-series measurement data.

2.3. Image acquisition

UV-induced fluorescence images (FL images) and reflectance images (CL images) were obtained from Day 1 under 365 nm UV light (LDL-71X12UV2-365-N, CCS Inc., Japan) with a light-emitting surface measuring 71×12 mm and using white light (LDL2-80X16SW2 (7800K), CCS Inc., Japan), respectively. A camera (DSLR, Kiss X10, Canon Inc., Japan) equipped with a lens (18–55 mm, with Image Stabilizer, Canon Inc., Japan), UV-cut filter (395 nm, Long Pass filter), and a polarizing filter (MCPL55, Marumi, Japan) were assembled on a steel frame as a machine vision system shown in Fig. 2. Kenko-Tokina (M105), a polarizing filter, was mounted on each LED and rotated to find a suitable angle that eliminates halation from the images (Cheng et al., 2015). At each interval, we captured both CL and FL images of each eggplant sample from two opposite sides. First, an image was taken from one side of the sample; then, the sample was rotated 180° around its longitudinal axis, and a second image was taken from the opposite side. All images were captured at a focal length of 35 mm. Imaging both sides of the sample allowed us to account for any asymmetrical features or variations in texture and color that might affect the analysis.

The CL images were obtained at a shutter speed of $1/4$ s, $f/7.1$, ISO 1600, and the FL images were obtained at a shutter speed of 2 s, $f/7.1$,

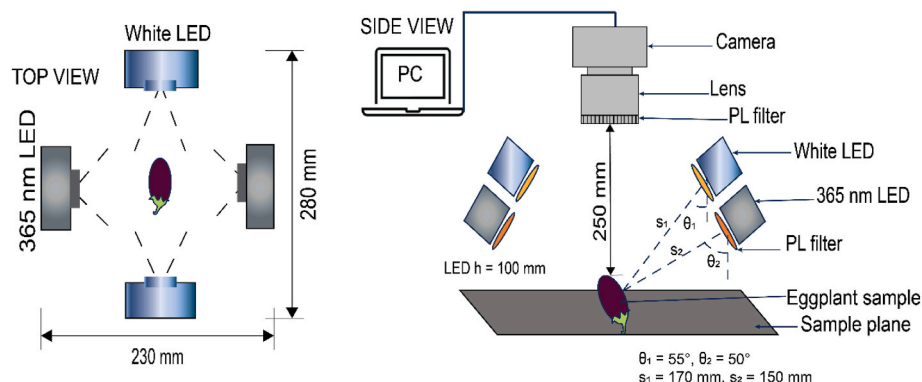


Fig. 2. Image acquisition geometry (camera WD = 250 mm; LED height $h = 100$ mm; incidence angles: white LED = 55° , 365 nm LED = 50°).

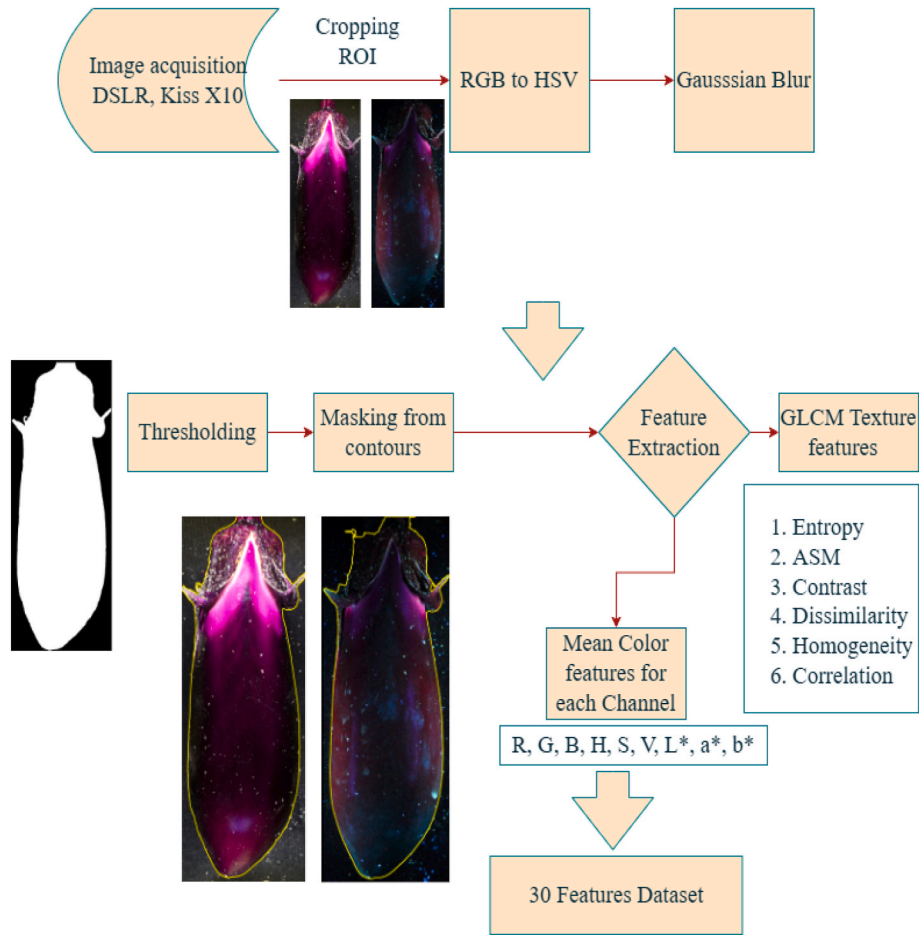


Fig. 3. Feature extraction algorithm steps. Features include mean color channels (R, G, B, H, S, V, L*, a*, b*) and six GLCM texture indices (contrast, dissimilarity, homogeneity, correlation, ASM, entropy) to form a 30-feature dataset. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

and ISO 6400. The resolution of each captured image had a height and width of 6000 pixels and 4000 pixels, respectively. The working distance from the front of the lens to the sample was 250 mm. Two white LEDs at 55° incidence (along-beam 170 mm; pair spacing 280 mm) and two 365 nm LEDs at 50° (along-beam 150 mm; spacing 230 mm) were mounted 100 mm above the sample plane. Both LED heights were 100 mm above the sample plane. The white balance was adjusted each time before measurement started using a white balance card.

2.4. Feature extraction algorithm

The image analysis used the OpenCV backend due to its extensive library support for image processing (Bradski, 2000). The first operation was to select the region of interest (ROI) by reducing the width to 1500 pixels and the height to 4000 pixels, as shown in Fig. 3. This was important in making sure that the important aspect of the image was highlighted while the other, less important part was eliminated. The images were then cropped and transformed into the HSV color space. The existing techniques utilize the HSV model that separates the image into the color information (H and S) and the brightness component (V). This color representation is closer to human perception and is more suitable for many applications, such as object detection, segmentation, and color analysis (Gonzalez & Woods, 2018).

After this conversion, each image was subject to Gaussian blurring to smooth out the noise and enable thresholding. Gaussian blurring applies a Gaussian function to the image defined as:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (1)$$

where x and y are the pixel coordinates, and σ is the standard deviation. This process reduces high-frequency noise while preserving the edges of objects.

Thresholding was then performed on the HSV images to create a binary mask that separates the eggplant region from the surrounding area. The thresholding operation can be represented as:

$$M(x, y) = 1 \text{ if } T_{\text{low}} \leq I_{\text{HSV}}(x, y) \leq T_{\text{high}}, \text{ otherwise } 0 \quad (2)$$

where $I_{\text{HSV}}(x, y)$ is the intensity of the pixel at coordinates (x, y) in the HSV image, T_{low} and T_{high} are the lower and upper threshold values, respectively, and $M(x, y)$ is the resulting binary mask.

Morphological closing was then used to smooth the mask's edges and fill gaps in the segmented area. This process involved a sequence of dilation operations followed by erosion operations using a kernel size of 5×5 .

$$C(I) = (I \oplus K) \ominus K \quad (3)$$

where I is the input image, K is the structuring element (kernel), $\oplus$ denotes the dilation operation, and $\ominus$ denotes the erosion operation. Dilation adds pixels to the boundaries of objects in the image, effectively "growing" the object and filling small holes and gaps. Erosion removes pixels from the object boundaries, "shrinking" the object slightly. Combined, these operations smooth the object boundaries and fill small

Table 2
Summary of features extracted.

Feature category	Features	Description	Relevance
Color Features (Reflectance (CL) and Fluorescence (FL))	Mean RGB	Mean of Red, Green, and Blue channels	Assess overall color distribution and variability; important for detecting changes due to water loss or spoilage
	Mean HSV	Mean of Hue, Saturation, and Value channels	Reflect changes in color perception and brightness; useful for analyzing storage effects
	Mean CIE L*a*b*	Means of L*, a*, and b* channels	Provide perceptual uniformity; detect subtle color differences indicative of quality changes
Texture Features	GLCM Features	Contrast, Dissimilarity, Homogeneity, ASM, Entropy, and Correlation derived from GLCM analysis	Quantify surface texture changes due to water loss and degradation during storage

holes without significantly altering the object's shape.

Refining the binary mask by median filtering eliminated the remaining “salt-and-pepper” noise. Median filtering replaces each pixel's value with the median value of the pixels in its neighborhood, effectively removing outliers while preserving edges (Bhargava & Bansal, 2021; Utiku & Köksel, 1998). The eggplant region was extracted from the original image using a bitwise AND operation:

$$I_{\text{seg}}(x, y) = I(x, y) \wedge \neg M(x, y) \quad (4)$$

where $I_{\text{seg}}(x, y)$ is the segmented image, $I(x, y)$ is the original image, $M(x, y)$ is the mask, and $\neg M(x, y)$ is the inverted mask. The operation retains only the pixels corresponding to the eggplant region while setting the background pixels to zero. The accuracy of the segmented region was verified by overlaying contours on the original image to confirm the precision of the segmentation process.

The whole body of the fruit, including the calyx, was used for image analysis because the characteristic fluorescence properties might affect the overall fluorescence as well as texture features. We extracted color, fluorescence, and textural features from the RGB, HSV, and CIE 1976 L*a*b* color spaces. The RGB color space is widely applied in digital imaging and hardware representation; HSV is closer to the human vision by distinguishing the chromatic information and intensity; the CIE 1976 L*a*b* is a perceptual color model that is particularly suitable for color comparison and discrimination by also separating the Intensity channel (Gonzalez & Woods, 2018).

Since changes in eggplants during storage are multifaceted, a comprehensive set of features is needed (as summarized in Table 2). Color features from RGB, HSV, and CIE Lab color spaces detect subtle pigmentation and brightness changes indicative of water loss, lignin accumulation, and textural degradation. Physiological changes not visible under normal lighting conditions, such as stress responses correlated with lignin production, are revealed through fluorescence features. Alterations in surface structure due to dehydration and spoilage are quantified through texture features derived from GLCM analysis. We try to increase the robustness of our predictive models and to give a more accurate estimate of eggplant quality during postharvest storage by utilizing a diverse set of features. Previous studies also show the significance of multiple features in creating quality assessments (Al Riza et al., 2023).

Texture analysis used a gray-level co-occurrence matrix (GLCM), incorporating Haralick's texture features. The GLCM for each grayscale image was computed at four orientations: 0°, 45°, 90°, and 135°, using a pixel distance of one. The mathematical representation for computing

the GLCM is:

$$P_{\theta}(i, j) = \sum_{x, y} I(x, y) \cdot I(x + \Delta x, y + \Delta y) \quad (5)$$

where θ represents the angle (0°, 45°, 90°, and 135°), Δx and Δy are displacements based on the pixel distance and orientation, and $I(x, y)$ is the intensity at pixel (x, y) . To stabilize the texture description against rotational variations, each texture feature was averaged across these four orientations. Six commonly utilized texture features were extracted:

$$\text{Contrast} = \sum_{i, j} P(i, j) \cdot (i - j)^2 \quad (6)$$

$$\text{Dissimilarity} = \sum_{i, j} P(i, j) \cdot |i - j| \quad (7)$$

$$\text{Homogeneity} = \sum_{i, j} \frac{P(i, j)}{1 + (i - j)^2} \quad (8)$$

$$\text{ASM} = \sum_{i, j} P(i, j)^2 \quad (9)$$

$$\text{Entropy} = - \sum_{i, j} P(i, j) \log P(i, j)$$

$$\text{Correlation} = \frac{\sum_{i, j} (i - \mu_i)(j - \mu_j)P(i, j)}{\sigma_i \sigma_j} \quad (10)$$

where μ_i , μ_j and σ_i , σ_j are the means and standard deviations of the row and column sums of the matrix, respectively. These features were calculated as the average of properties generated from all GLCM orientations, as outlined in Haralick's seminal paper (Haralick et al., 1973). Their proven use influenced the selection of these six texture features in prior studies on color texture analysis (Al Riza et al., 2023; Drimbarean & Whelan, 2001; Humeau-Heurtier, 2022).

2.5. Statistical and multivariate analysis

The data was analyzed, and predictive models for eggplant quality assessment during storage were developed using a variety of statistical and multivariate techniques.

2.5.1. Partial Least Squares Regression (PLSR)

The relationship between the weight loss of eggplants during storage and the extracted color and texture features was modeled using Partial Least Squares Regression (PLSR). PLSR is especially convenient when dealing with multiple predictor variables that may be highly collinear, as is frequently the case with spectral and image data. Using 5-fold cross-validation, the optimal number of latent variables was determined to prevent overfitting. All samples were used for model calibration, with performance evaluated through cross-validation.

2.5.2. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) was used as a supervised classification method to differentiate between eggplants stored under different temperature and humidity conditions. Linear Discriminant Analysis (LDA) operates by identifying linear combinations of features that optimize class separation and minimize intra-class variance. The LDA model's performance was evaluated with Leave-One-Group-Out (LOGO) cross-validation to ensure that all observations from each unique sample were kept together during model training and evaluation.

2.5.3. Support Vector Machines (SVMs)

Classification of the eggplants based on the storage conditions was also done using Support Vector Machines (SVM). SVM is a powerful

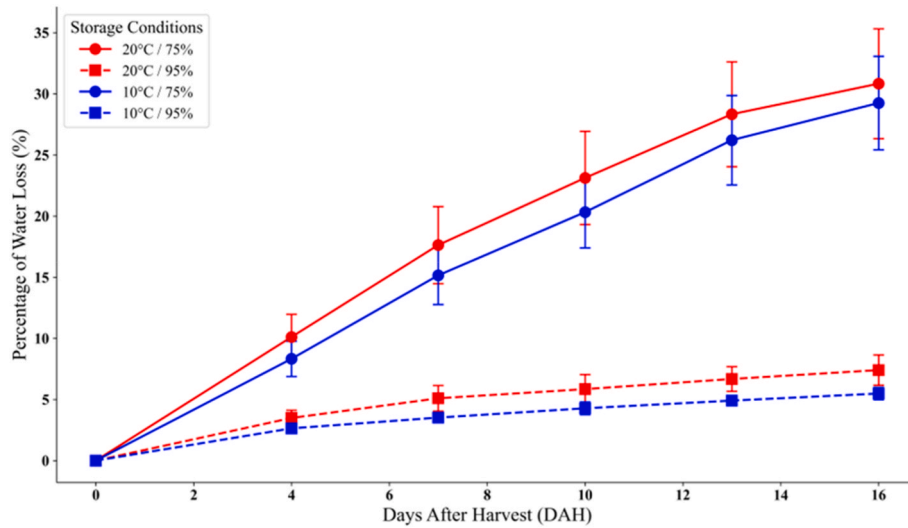


Fig. 4. Water loss in eggplants stored under different temperature and humidity conditions.

machine learning algorithm that categorizes the features into separate groups based on the best hyperplane in a multi-dimensional space. For this study, we employed a support vector machine (SVM) with a radial basis function (RBF) kernel, and the parameters C and gamma were set at 1 and 'scale', respectively. The SVM model was evaluated using LOGO cross-validation (Schölkopf & Smola, 2001). The classification performance metrics, such as

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (11)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (12)$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (13)$$

were computed in each of the storage conditions, where TP, FP, and FN are the true positives, false positives, and false negatives, respectively.

2.5.4. Model robustness analysis

To assess the robustness of the models, LDA and SVM classifiers were trained with stratified random subsampling (10–40 samples, 30 repetitions per sample) and with class imbalance conditions (balanced to 10:1 ratios) using the Leave One Group Out (LOGO) cross-validation on each setup (He & Garcia, 2009; Kohavi, 1995).

2.5.5. Analysis of Covariance (ANCOVA)

To test whether an early fluorescence descriptor can predict cumulative water loss (WL [%]) at day 10, we fitted an analysis of covariance (ANCOVA) with storage treatment category as a four-level categorical factor and a single Day-1 fluorescence feature as the covariate. Four outlier samples were excluded per category, resulting in a balanced dataset of 40 samples. WL (%) at Day 10 was computed per fruit as:

$$\text{WL}(\%) = 100 \times \frac{W_{\text{Day-1}} - W_{\text{Day-10}}}{W_{\text{Day-1}}} \quad (14)$$

The treatment categories correspond to the four temperature/RH regimes (10 °C/95 % RH, 20 °C/95 % RH, 20 °C/75 % RH, 10 °C/75 % RH). The model used ordinary least squares with category-specific intercepts and slopes via interaction terms (Kutner et al., 2005):

$$\text{WL}_i(\%) = \alpha_{c[i]} + \beta_{c[i]} zX_i + \varepsilon_i \quad (15)$$

where, $c[i]$ is the treatment category of sample i ; α_c and β_c are the

category-specific intercept and slope, while ε_i is the residual error. zX denotes the Day-1 fluorescence feature standardized (zero mean, unit variance) within each LOOCV training fold. The specific Day-1 index is selected in Section 3.5. Validation used leave-one-out cross-validation (LOOCV) (Hastie et al., 2009).

2.5.6. Data preprocessing

For each sample, features extracted from both sides were averaged to obtain a single representative feature vector per time point. All the data collected on the different measurement dates were combined into one dataset. This led to having several data points for each sample, where each data point was captured at a certain time. The data were also preprocessed to have a zero mean and unit variance as estimated from the features. This is done through Z-score normalization, where the data is transformed such that the average of each attribute is zero and the standard deviation is one. Normalization is important to both PLSR and classification algorithms because large-scale features may dominate the results and affect the model in a way that features with small but important information may overshadow other features. (Aksoy & Haralick, 2001; Hastie et al., 2009). For all cross-validated models (PLSR, LDA, SVM), scaling and any feature selection were refit within each training fold.

2.5.7. Tools

All statistical analyses and classification models were implemented using Python (3.12.4), OpenCV 4.10 for image processing, the scikit-learn library 1.5.1 (Pedregosa et al., 2011) for model development and evaluation, pandas 2.2.2 (McKinney, 2010) for data manipulation, and matplotlib 3.10.7 (Hunter, 2007) for visualization. ANCOVA implementation used statsmodels 0.14.4 for OLS (Seabold & Perktold, 2010).

3. Results and discussion

3.1. Water loss

The weight of eggplants was measured regularly to monitor water loss under varying temperature and humidity conditions (10 °C and 20 °C, with 75 % and 95 % relative humidity). As seen in Fig. 4, eggplants exposed to a temperature of 20 °C and 75 % relative humidity lost the most water, while those stored at 10 °C and 95 % RH lost the least. At the end of the storage period, the eggplants stored at 20 °C and 75 % RH lost nearly 30 % of their initial weight, whereas the ones at 10 °C and 95 % RH only reduced by 5 %. High temperatures (20 °C) increase the

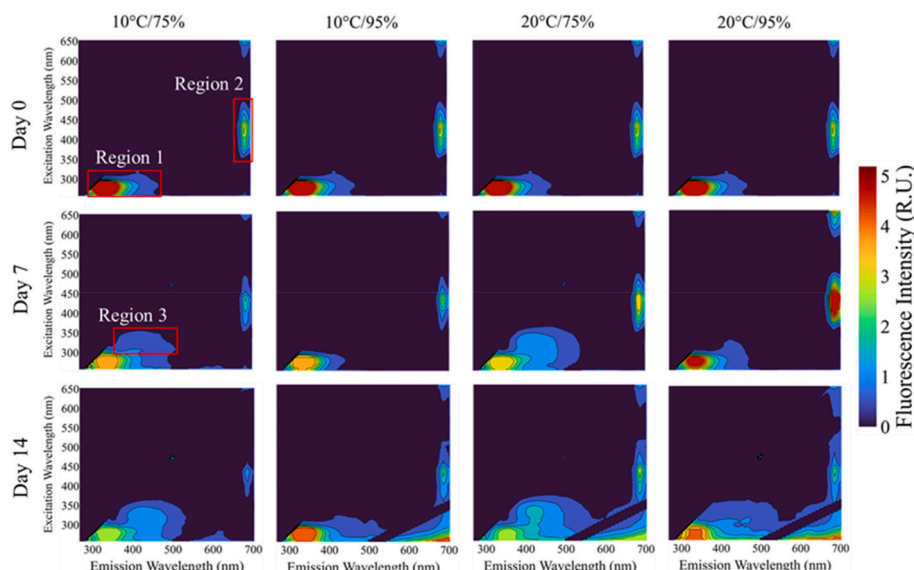


Fig. 5. Eggplant Excitation-Emission Matrix during storage, EEM plots use emission on the x-axis and excitation on the y-axis, intensity in Raman Units (R.U.).

kinetic energy of water molecules, which accelerates evaporation and transpiration rates (Ben-Yehoshua & Rodov, 2002). Low humidity (75 %) also creates a higher vapor pressure deficit (VPD), which increases the water vapor diffusion rates from the fruit (Paull, 1999). However, at lower temperatures (10 °C) and higher relative humidity (95 %), the low VPD decreases water evaporation as the environment around the product is more humid, keeping eggplants compact (Díaz-Pérez, 1998). This retention helps to reduce stress reactions associated with dehydration, including the formation of lignin, which occurs under more severe conditions. At 95 % relative humidity and even at relatively high temperatures, the surrounding moisture alleviates the pressure on the tissues of the eggplant due to transpiration. Thus, the water content in the tissues is higher. This implies that the benefit of high humidity is enough to suppress the dryness caused by high temperatures. However, it is also important to note that a very high increase in humidity is favorable for rotting and microbes, offsetting gains from reduced transpiration (Gidado et al., 2024).

3.2. Fluorescence EEM

Fig. 5 shows the characteristic EEM for eggplants before and after storage. Three distinct regions can be identified: Region 1 (Excitation

(Ex) wavelength 280 nm, Emission (Em) wavelength 330 nm), Region 2 (Ex/Em peak: 435 nm/680 nm), and Region 3 (Ex/Em peak: 365 nm/420 nm). The peak in Region 1 was attributed to protein-like (tryptophan) compounds responsible for the nutrition derived from eggplants. (Ladokhin, 2006; Stedmon et al., 2003). Region 2 is linked to the chlorophyll pigment. (Nedbal & Whitmarsh, 2004; Nie et al., 2020). Region 3 (Ex/Em $\approx$ 365/420 nm) corresponds to a blue–green phenolics/lignin band; we therefore treat it as a stress-linked autofluorescence band that includes lignin signatures rather than a lignin-only marker (Choong et al., 2016; Donaldson, 2020; Lichtenthaler, 2021; Rai et al., 2017). This research is interested in Region 3 due to its inherent potential for quality monitoring of eggplants during storage. Lignin is a complex organic polymer found in the plant cell walls, contributing to their rigidity and structural integrity. Lignin's fluorescence is typically observed in the blue to green emission range when excited in the UV to the visible range. Our analysis revealed that the fluorescence intensity in Region 3 increased over the storage period, especially in eggplants stored at 20 °C and 75 % RH.

3.3. Changes in region 3 fluorescence peak

Fig. 6 shows the changes in Region 3 (Excitation wavelength/

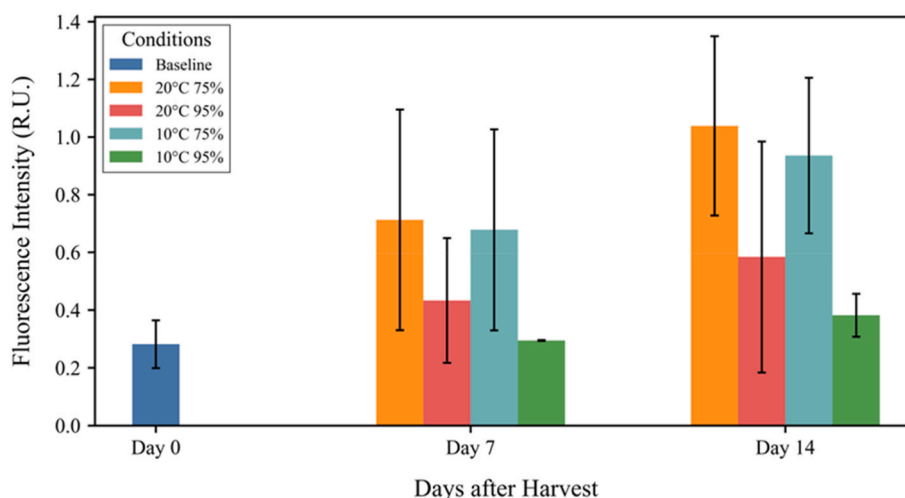


Fig. 6. Region 3 (Ex/Em = 365/420 nm) fluorescence intensity (R.U.) versus time (baseline (Day 0), Day 7, Day 14) under each storage condition (mean $\pm$ SD).

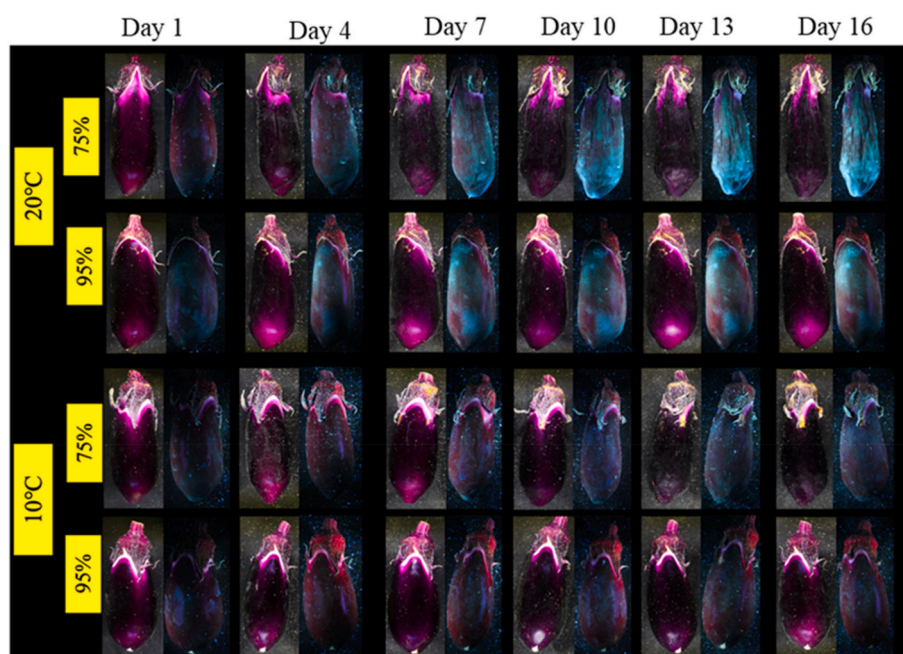


Fig. 7. Color and FL image changes during storage. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Emission wavelength peak: 365 nm/420 nm). The baseline represents the first day of measurement obtained from the top, center, and bottom parts of the eggplant fruit. Phenylpropanoid-pathway activity (including lignification) may be stimulated during storage in response to damage or stress. As illustrated in Fig. 6, eggplants kept at 20 °C and 75 % humidity showed a notable rise in the lignin fluorescence peak compared to the baseline (first day of measurement), suggesting that this environment promotes lignin production. In contrast, eggplants stored at 10 °C and 95 % RH showed marginal change in Region 3 fluorescence, indicating lower stress and lower lignin synthesis. Additionally, at 20 °C, higher humidity (95 % RH) caused significantly lower lignin fluorescence than lower humidity (75 % RH), suggesting that high humidity can offset temperature-induced stress and reduce lignin production. For example, at 10 °C, lower lignin fluorescence peaks were seen in eggplants stored at 75 % RH relative to 20 °C storage, again indicating that lower temperatures inhibit lignin synthesis. In line with the previous research, time-dependent lignin deposition with an initial peak in phenylalanine ammonia-lyase (PAL) activity and a continued rise in cinnamyl alcohol dehydrogenase (CAD) and peroxidase (POD) activities observed in loquat held at 20 °C (Cai et al., 2006a), with dehydration stimulating lignin deposition in loquat pericarp (Zhu et al., 2021). Similarly, our Region 3 increased during storage, but most at 20 °C/75 % RH and least at 10 °C/95 % RH (Fig. 6).

3.4. Image changes over time

Fig. 7 shows color and UV-induced fluorescence images under different temperature and humidity conditions. At first glance, eggplants have a glossy texture and a vivid purple color. The FL images show an increase in blue-white fluorescence at 20 °C, a noticeable loss of brightness, and the beginning of shrinkage, mostly at 75 % humidity. It originates from phenolic compounds and lignin precursors that emit at 420 nm. At 20 °C/75 % RH, respiration and the phenyl-propanoid pathway run faster; phenolics oxidize and polymerize, so mean Blue rises sharply even before WL reaches 20 %. In contrast, at 10 °C/75 % RH, the fruit actually loses more water by Day-10, but enzymes such as polyphenol oxidase and peroxidase are temperature-limited, the peel stays intact, and fluorescence remains lower (Cai et al., 2006b; Doğan

et al., 2002). Thus, when dehydration is held constant, the fluorescence evidence confirms that eggplants stored at 10 °C retain superior peel quality compared with those at 20 °C.

This is primarily associated with the Region 3 fluorescence observed in the EEM data, as shown in Figs. 5 and 6, which is linked to lignin production. Reduced turgor pressure and water loss in the plant tissues are linked to quicker moisture loss and quality degradation (Burdon & Clark, 2001). Elevated temperatures can potentially hasten several metabolic processes, such as pigment degradation. Dehydration from low humidity makes the skin of the eggplants wrinkle and lose its vibrancy (Moretti et al., 2010). The purple hue of eggplants is attributed to anthocyanin pigments, which deteriorate with time and are susceptible to environmental changes. It has been demonstrated that high temperatures hasten the anthocyanins' disintegration, making the eggplants' appearance look less vibrant (Condurache et al., 2021).

On the other hand, eggplants kept at 10 °C and 95 % relative humidity for an extended period keep their bright color and firmness. Fruits and vegetables usually respire more slowly at lower temperatures, which helps to preserve their quality and increase their shelf life and marketability. However, keeping humidity levels high is bad since it produces a damp atmosphere that promotes microbial development and spoiling (Grierson & Wardowski, 1978). Fruit physiological states and activities not visible on reflectance images are revealed by fluorescence imaging. The blue-white fluorescence increases drastically at low humidity (75 %) and high temperature (20 °C), suggesting stress reactions and lignin buildup. Fruits fortify their cell walls by depositing lignin in response to dehydration, which lowers water loss and improves structural integrity. This defensive mechanism can cause increased lignin biosynthesis (Mulas et al., 1996).

3.5. PLSR modeling for water loss estimation

Partial Least Squares Regression (PLSR) was used to examine the features that were obtained. By locating latent variables (LVs) that capture the most pertinent variation associated with the response variable, PLSR can decrease the complexity of the dataset and simplify the analysis without compromising the accuracy of the data (Al Riza et al., 2023). The retrieved features were normalized before being analyzed to

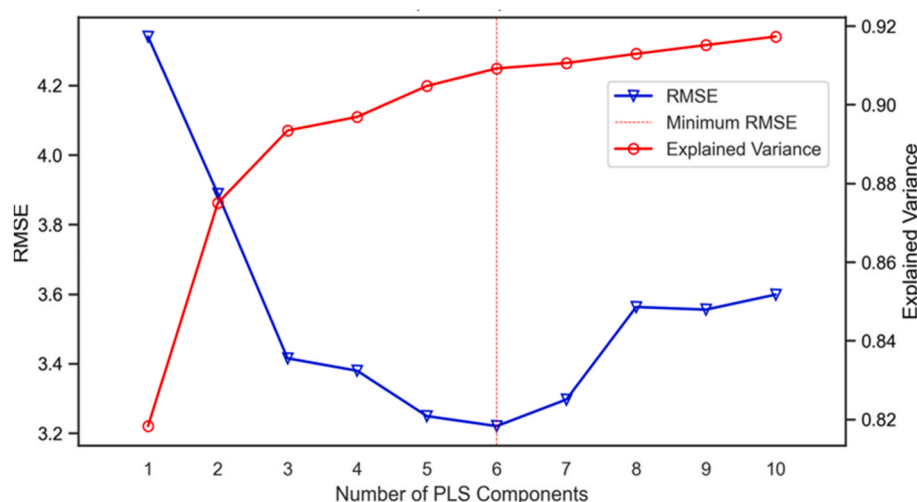


Fig. 8. PLS component optimization. Cross-validated RMSE (left axis) and explained variance R^2 (right axis) versus number of components; the minimum RMSE occurs at six components.

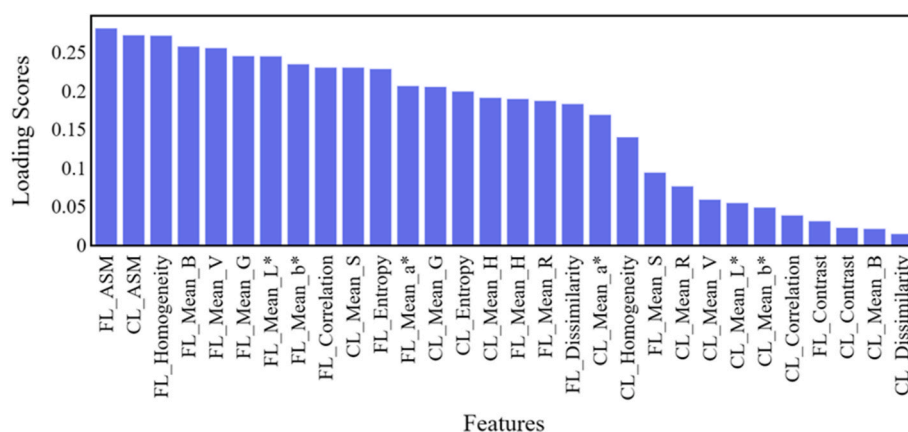


Fig. 9. Sorted loading scores for extracted features.

Table 3

Performance metrics of different feature sets.

Feature set	R^2_{train}	R^2_{cv}	RMSEC	RMSECV	Features
Selected features (6)	0.890	0.884	3.306	3.470	6
Reflectance color + texture	0.832	0.818	4.075	4.254	15
All color features	0.837	0.814	4.013	4.296	18
FL color + texture	0.827	0.808	4.140	4.374	15
Only fluorescence texture	0.749	0.738	4.990	5.102	6
All texture features	0.757	0.737	4.916	5.116	12
Only fluorescence color	0.745	0.717	5.038	5.305	9
All features	0.725	0.710	5.220	5.364	30
Only reflectance texture	0.680	0.661	5.633	5.802	6
Only reflectance color	0.655	0.636	5.856	6.014	9

prevent scale differences from biasing the model. By establishing a correlation between the target variable, weight loss, and the extracted features, the first PLSR model was fitted using 5-fold cross-validation.

As shown in Fig. 8, the Root Mean Square Error (RMSE) and the Explained Variance (R^2) were a reference for choosing the number of components. As more components were added, the RMSE gradually dropped, indicating an improvement in the predicted accuracy of the model. The RMSE increased after six components, indicating overfitting in cases where more than six are utilized. Because of this, 6 PLS components are the ideal amount for this model, where the RMSE is lowest and the explained variance in the data is high enough. The features were

ranked according to their loading values to identify which features had the most significant influence on the model's weight loss prediction, as shown in Fig. 9. The best 6 features with absolute loading values (loading ≥ 0.238) were selected. Cross-validation indicated that this 6-feature subset had greater predictive performance than the models with full 30 features as illustrated in Table 3. The texture features ASM for the fluorescence image, ASM for the reflectance image, and Homogeneity for the fluorescence image and reflectance image features, mean blue value for the fluorescence image, mean V, HSV value for the fluorescence image, and the mean green value for the fluorescence image have the highest loading scores. The performance of the final PLSR model based on these six features is shown in Fig. 10.

The changes in the uniformity of the eggplant surface during storage due to water loss are indicated by the important ASM in the reflectance and fluorescence images. The internal structure of the peel and its bioactive chemicals, which respond to physiological stress and degradation, are related to the homogeneity of the fluorescence image. As fruits reinforce their cell walls to prevent water loss and boost structural integrity, water loss causes an increase in the production of lignin (Mulas et al., 1996; Paull, 1999; Vanholme et al., 2019).

Because of the noticeable rise in blue-white fluorescence in the images, two essential features are the average intensity of the blue color (RGB) and brightness (value) in the HSV color space. This fluorescence is a sign of storage-related alterations in the eggplants. Due to the strong correlation between these characteristics and lignin production, the

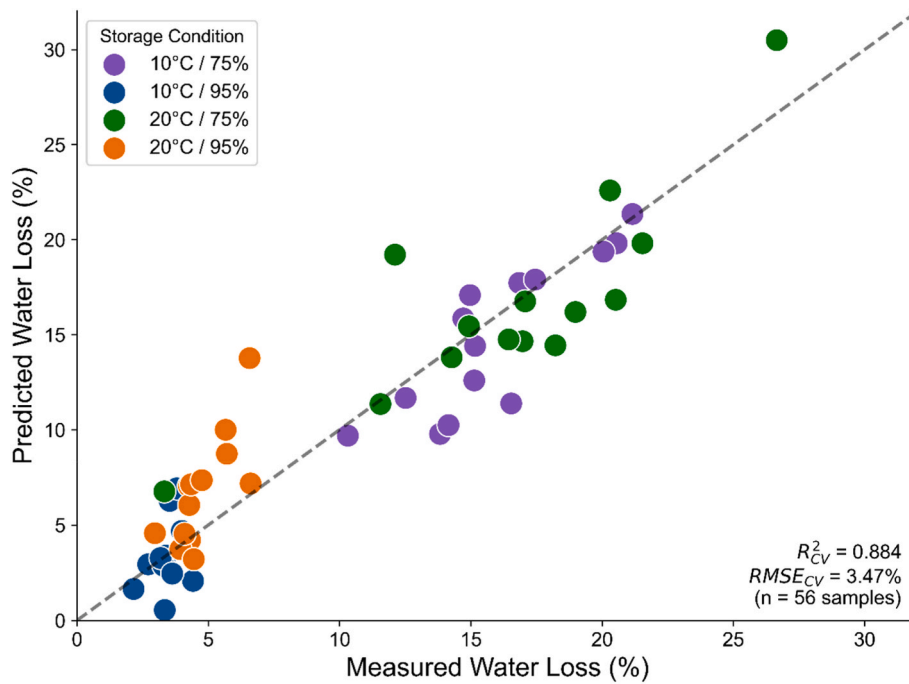


Fig. 10. PLSR model performance for water loss prediction.

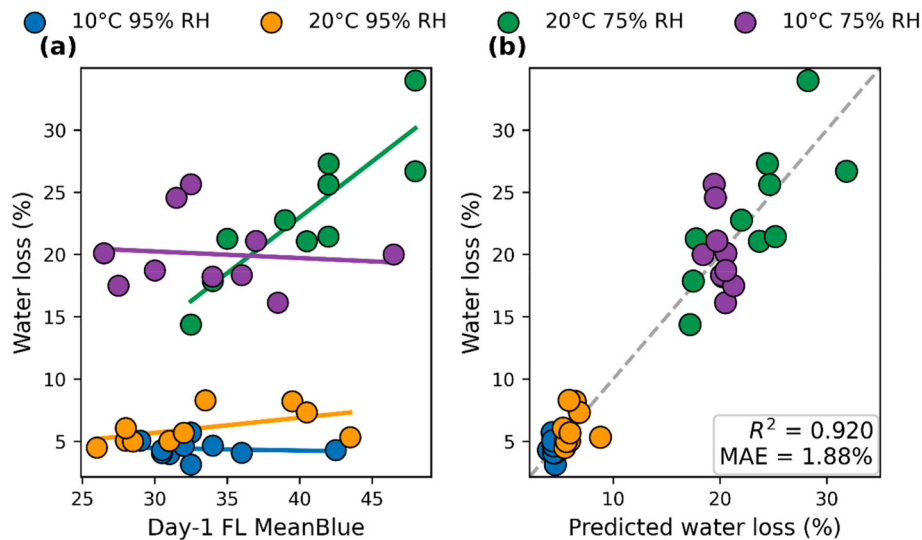


Fig. 11. (a) WL at Day 10 versus Day 1 FL_MeanBlue with per-category least-squares lines (Eq. (15)); (b) LOOCV predicted versus observed WL.

mean green value also considerably assesses eggplant quality. Since lignin fluoresces in the blue and green regions, the eggplant peel's mean blue and green values are essential markers of lignin content (Donaldson, 2020; Rai et al., 2017). By monitoring these fluorescence characteristics, one can effectively assess eggplants' stress levels and

Table 4

Eq. (15) coefficients by treatment category for WL at Day 10; full-sample OLS; covariate z-standardized; values are estimates with 95 % Confidence Intervals (CI).

Treatment category	α	β (per 1 SD)	β 95 % CI
10 °C/95 % RH	4.36	−0.12	−2.38–2.15
20 °C/95 % RH	6.37	0.54	−0.82–1.90
20 °C/75 % RH	18.39	5.38	3.75–7.01
10 °C/75 % RH	19.99	−0.32	−1.80–1.16

overall quality during storage non-invasively.

The performance of several feature sets utilized in result prediction using PLSR models is shown in Table 3, evaluated through 5-fold cross-validation. The “Selected Features (6)” subset stands out because it uses only six features, as opposed to all 30 features. This subset yielded an R^2 value of 0.884 in cross-validation (R^2_{CV}), with a Root Mean Square Error of Cross-Validation (RMSECV) of 3.47 %. These are the first six features shown in Fig. 9. Most of these features are textural and fluorescence imaging features, indicating that they are the most important for assessing the quality of eggplants while they are being stored.

3.6. Water loss prediction

We asked whether a single Day-1 fluorescence feature could forecast cumulative water loss (WL) at Day 10. We fitted an ANCOVA with treatment category (10 °C/95 % RH, 20 °C/95 % RH, 20 °C/75 % RH,

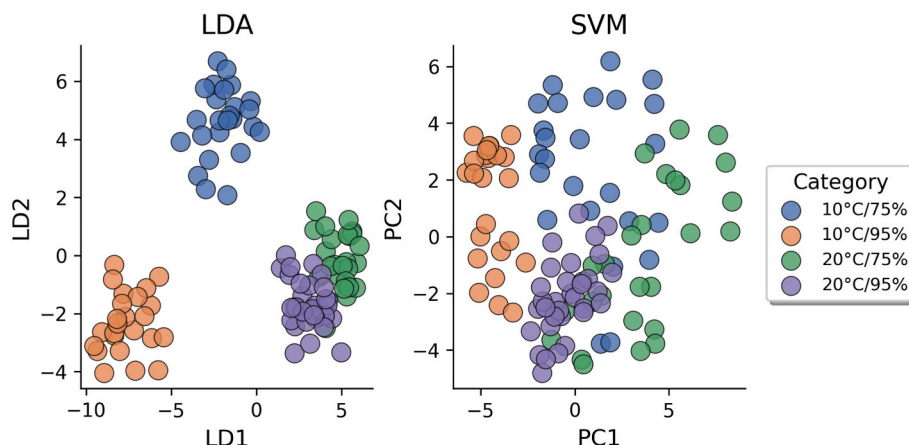


Fig. 12. Classification of storage conditions using LDA and SVM; Models were evaluated using Leave-One-Group-Out cross-validation on 108 observations from 40 unique samples (10 °C/75 %: 10; 10 °C/95 %: 9; 20 °C/75 %: 10; 20 °C/95 %: 11 samples); LDA (LD2 vs LD1) and SVM (PC2 vs PC1 for visualization).

10 °C/75 % RH) as a factor and the Day-1 mean blue intensity from fluorescence images (FL_MeanBlue) as the sole covariate (ordinary least squares; LOOCV with the covariate z-standardized within each training fold). Fig. 11 (a) makes the key point at a glance: WL at Day 10 rises with the Day-1 blue-band fluorescence index (FL_MeanBlue) only in some environments, not all. The four fitted lines are not parallel and have different intercepts, so a single global line would be biased. This pattern mandates conditioning on environment via the interaction in Eq. (15) (Treatment Category $\times$ Day-1 index). The fitted coefficients from Eq. (15) (full-sample OLS, covariate z-standardized; $\mu = 34.89$, $\sigma = 6.00$) are reported in Table 4. The baselines (α) differ strongly by treatment category (4–6 % at 10 °C/95 % RH vs 18–20 % at 20 °C/75 % RH), and, critically, the response (β) is category-dependent; 20 °C/75 % RH shows a clear positive slope ($\beta = 5.38$, 95 % CI = 3.75–7.01), whereas both 10 °C categories are flat and 20 °C/95 % RH is weak and non-significant. In short, Day-1 blue fluorescence is a useful early predictor only under warm, dry storage; elsewhere, it adds little signal, which is exactly what Fig. 11(a) reveals.

The model achieved $R^2_{\text{LOOCV}} = 0.92$ and $\text{MAE} = 1.88$ % (Fig. 11 (b)). When conditioned on the correct treatment category, the single-index model generalizes well and provides precise early forecasts of Day-10 WL. In the warm/dry category (20 °C/75 % RH), where Vapor Pressure Deficit (VPD) is highest, fruit with larger Day-1 blue fluorescence lost more water by Day 10. At 20 °C/95 % RH, the slope remained positive but weaker, consistent with lower evaporative demand (VPD). At 10 °C/75 % RH, the slope was essentially flat, suggesting that variation in WL at low temperature is driven mainly by physical transport under moderate VPD rather than by the Day-1 blue-fluorescence signal.

The predictive ability difference between Day-1 fluorescence under different storage conditions can be explained by two factors. First, vapor pressure deficit (VPD): at 95 % RH, little water loss is observed irrespective of initial fluorescence state, so it does not have predictive power. Second, temperature-dependent metabolism: at 20 °C/75 % RH, the phenyl-propanoid pathway remains active (Section 3.4), allowing Day-1 fluorescence to reflect biochemical states that determine subsequent water loss rates among fruits. At 10 °C/75 % RH, although moderate VPD creates transpiration pressure, enzyme activity is temperature-limited (Cai et al., 2006a; Doğan et al., 2002). The variation in Day-10 water loss becomes driven by physical transport properties rather than the Day-1 fluorescence signal. Therefore, the covariate is predictive only where both sufficient VPD and active metabolism create condition-specific biological variation in water loss.

3.7. Classification of storage conditions

The LDA and SVM models provided mean cross-validation accuracies

Table 5

Performance for Leave-One-Group-Out cross-validation Comparison of LDA and SVM Models; (P/R/F1) is shorthand for (Precision/Recall/F1-score).

Metric	LDA			SVM		
Mean CV score	0.944			0.852		
Total observations	108			108		
Unique samples	40			40		
Category (P/R/F1)	P	R	F1	P	R	F1
10 °C/75 %	1.00	0.96	0.98	0.96	0.96	0.96
10 °C/95 %	0.96	1.00	0.98	1.00	1.00	1.00
20 °C/75 %	0.96	0.85	0.90	0.89	0.65	0.76
20 °C/95 %	0.89	0.97	0.93	0.78	0.94	0.85
Macro Avg (P/R/F1)	0.95	0.94	0.95	0.91	0.89	0.89
Weighted Avg (P/R/F1)	0.95	0.94	0.94	0.90	0.89	0.89

of 0.944 and 0.852, respectively. These high results suggest that both classifiers have a high level of accuracy in distinguishing eggplants according to their storage conditions, with LDA marginally outperforming the other.

Fig. 12 illustrates the classification results using LDA and SVM. For the LDA plot (left), the data is projected onto the first two Linear Discriminant (LD) components. For the SVM plot (right), the dataset is projected onto the first two Principal Components (PCs) for visualization purposes. SVM does not inherently provide a low-dimensional representation as LDA does (Muñoz & González, 2010). Tables 5 and 6 show the classification performance and confusion matrices for each storage condition. Both models showed good performance in classifying samples stored at 10 °C with both humidity levels. The classification errors occurred between the two 20 °C storage conditions. For LDA, four samples of 20 °C/75 % RH were misclassified as 20 °C/95 % RH, and one sample of 20 °C/95 % RH was misclassified as 20 °C/75 % RH. For SVM, 7 samples of 20 °C/75 % RH were misclassified as 20 °C/95 % RH, with no errors in the opposite direction. The misclassification pattern between the two 20 °C storage conditions can be explained by the dominance of fluorescence features in the LDA model. Both 20 °C/75 % RH and 20 °C/95 % RH showed similar Region 3 fluorescence increases through Day 7 (Fig. 6), indicating temperature-induced phenolic metabolism, while differing in cumulative water loss (Fig. 4). Since the most important LDA features were fluorescence-based, samples from these two conditions with comparable fluorescence levels but different hydration states overlap in the discriminant space. In contrast, 10 °C conditions showed lower fluorescence responses and were separated with higher accuracy. We tested the strength of the classifiers by evaluating their performance under different training sample sizes and class-imbalance conditions (see Table 7a and 7b).

Table 6

Confusion matrices for LDA and SVM models.

Actual/Predicted	LDA				SVM			
	10 °C/75 %	10 °C/95 %	20 °C/75 %	20 °C/95 %	10 °C/75 %	10 °C/95 %	20 °C/75 %	20 °C/95 %
10 °C/75 %	25	0	0	0	24	0	0	1
10 °C/95 %	0	24	0	0	0	24	0	0
20 °C/75 %	0	0	22	4	1	0	18	7
20 °C/95 %	0	0	1	32	0	0	7	26

Table 7a

Sample size robustness analysis.

Number of Samples	LDA	SVM
10	0.603 ± 0.178	0.524 ± 0.198
15	0.609 ± 0.148	0.706 ± 0.122
20	0.769 ± 0.102	0.804 ± 0.060
25	0.823 ± 0.071	0.830 ± 0.047
30	0.858 ± 0.055	0.849 ± 0.035
35	0.884 ± 0.031	0.848 ± 0.027
40	0.920 ± 0.014	0.850 ± 0.011

Table 7b

Class Imbalance Robustness; Sample Distribution notation (a, b, c, d) represents the relative number of samples from each of the four storage categories.

Sample Distribution	Balance	LDA	SVM
(1, 1, 1, 1)	Balanced	0.944	0.852
(2, 1, 1, 1)	Moderate	0.783	0.817
(3, 1, 1, 1)	High	0.935	0.957
(4, 2, 1, 1)	Severe	0.614	0.864
(10, 5, 2, 1)	Extreme	0.614	0.864

Category 0 = 10 °C/75 % RH, Category 1 = 10 °C/95 % RH.

Category 2 = 20 °C/75 % RH, Category 3 = 20 °C/95 % RH.

3.8. Practical applications

The Ex/Em = 365/420 nm region, consistent with phenolic/lignin-related autofluorescence, can anchor low-cost, UV imaging for real-time WL monitoring during storage and distribution. A six-feature PLSR provides WL estimates for inventory control (rank-ordering batches; prioritizing dispatch), while the single-index ANCOVA enables early forecasting in warm, low-RH chains. LDA/SVM classifiers can flag mismatched storage regimes at intake. Selecting transport and storage protocols that will provide optimal handling can minimize postharvest losses and extend shelf life.

4. Conclusion

Fluorescence spectroscopy and combined color and UV-induced fluorescence imaging were used in this work to identify and assess the quality of eggplant subjected to different temperature and humidity conditions during postharvest storage. We identified three distinct fluorescence regions in eggplant EEM, with the lignin-associated peak (Ex/Em: 365 nm/420 nm) serving as a potential stress indicator. The increased blue-white fluorescence in UV-induced images, particularly at 20 °C and 75 % humidity, correlated with water loss and textural degradation. A PLSR model ($R^2 = 0.884$) was developed to estimate water loss from combined color and texture features of fluorescence and reflectance images. Moreover, the LDA and the SVM models were able to distinguish between eggplants stored under different conditions with accuracies of 94.4 % and 85.2 %, respectively. These non-destructive methods show high potential for use in the real-time quality assessment of eggplants and their shelf-life estimation. A single-index model using Day-1 FL MeanBlue with category-specific slopes achieved LOOCV $R^2 = 0.920$ (MAE = 1.88 %), but its utility was category-dependent:

predictive in 20 °C/75 % RH, weak in 10 °C storage. Thus, early forecasting is achievable where dehydration dominates, while cooler chains benefit from multi-feature imaging. However, for these results to be fully validated, future studies should employ chemical assays (phenolics, anthocyanins, lignin markers) to apportion contributions to the blue band and to validate biomarkers. In order to test the generalizability and robustness of the model to real-life applications, further studies must incorporate external validation involving independent test sets of various harvest batches, different growing seasons, or geographical locations. This study also used constant temperature and humidity, which enabled systematic isolation of storage parameters. This is not a reflection of the dynamic environment experienced in commercial supply chains. Thus, validation in realistic variable conditions is necessary in the future. Additionally, since this experiment used one cultivar (cv. Senryo 2), subsequent studies must confirm performance in cultivars with varying peel anthocyanin and cuticular properties, which are known to vary UV-excited fluorescence baselines and water loss permeability, to ascertain if variety-specific calibration is required. This would enable a more accurate description of the behavior of fluorescence signals in relation to eggplant physiological changes during storage.

CRedit authorship contribution statement

Vincent Rotich: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tianqi Gao:** Writing – review & editing, Validation. **Panintorn Prempre:** Writing – review & editing, Validation. **Takahiro Hayashi:** Writing – review & editing, Validation, Project administration, Methodology, Conceptualization. **Kazuhiko Namba:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Mitsuji Monta:** Writing – review & editing, Validation, Resources. **Motomi Nishimoto:** Writing – review & editing, Validation, Resources, Funding acquisition, Conceptualization. **Naoshi Kondo:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The first author is very thankful to Omi Weighing Machine Inc. for the scholarship support during this study. We also thank JA Binan, Okayama prefecture, for providing us with the samples used in this study.

Data availability

Data will be made available on request.

References

- Aksoy, S., & Haralick, R. M. (2001). Feature normalization and likelihood-based similarity measures for image retrieval. *Pattern Recognition Letters*, 22(5), 563–582. [https://doi.org/10.1016/S0167-8655\(00\)00112-4](https://doi.org/10.1016/S0167-8655(00)00112-4)
- Al Riza, D. F., Rulin, C., Tun, N. T. T., Yi, P. P. L., Thwe, A. A., Myint, K. T., & Kondo, N. (2023). Mango (*Mangifera indica* cv. Sein Ta Lone) ripeness level prediction using color and textural features of combined reflectance-fluorescence images. *Journal of Agriculture and Food Research*, 11, Article 100477. <https://doi.org/10.1016/j.jafr.2022.100477>
- Albrecht, C. (2008). Joseph R. Lakowicz: Principles of fluorescence spectroscopy, 3rd edition. *Analytical and Bioanalytical Chemistry*, 390(5), 1223–1224. <https://doi.org/10.1007/s00216-007-1822-x>
- Babellahi, F., Amodio, M. L., Marini, F., Chaudhry, M. M. A., de Chiara, M. L. V., Mastrandrea, L., & Colelli, G. (2020). Using chemometrics to characterise and unravel the near infra-red spectral changes induced in aubergine fruit by chilling injury as influenced by storage time and temperature. *Biosystems Engineering*, 198, 137–146. <https://doi.org/10.1016/j.biosystemseng.2020.08.008>
- Ben-Yehoshua, S., & Rodov, V. (2002). Transpiration and water stress. In *Postharvest physiology and pathology of vegetables* (2nd ed.). CRC Press. <https://doi.org/10.1201/9780203910092.ch5>
- Bhargava, A., & Bansal, A. (2021). Fruits and vegetables quality evaluation using computer vision: A review. *Journal of King Saud University - Computer and Information Sciences*, 33(3), 243–257. <https://doi.org/10.1016/j.jksuci.2018.06.002>
- Bilger, W., Johnsen, T., & Schreiber, U. (2001). UV-excited chlorophyll fluorescence as a tool for the assessment of UV-protection by the epidermis of plants. *Journal of Experimental Botany*, 52(363), 2007–2014. <https://doi.org/10.1093/jexbot/52.363.2007>
- Bradski, G. (2000). The OpenCV Library. *Dr. Dobbs' Journal*, 25(11), 120–125.
- Burdon, J., & Clark, C. (2001). Effect of postharvest water loss on 'Hayward' kiwifruit water status. *Postharvest Biology and Technology*, 22(3), 215–225. [https://doi.org/10.1016/S0925-5214\(01\)00095-3](https://doi.org/10.1016/S0925-5214(01)00095-3)
- Cai, C., Xu, C., Li, X., Ferguson, I., & Chen, K. (2006a). Accumulation of lignin in relation to change in activities of lignification enzymes in loquat fruit flesh after harvest. *Postharvest Biology and Technology*, 40(2), 163–169. <https://doi.org/10.1016/j.postharvbio.2005.12.009>
- Cai, C., Xu, C., Shan, L., Li, X., Zhou, C., Zhang, W., Ferguson, I., & Chen, K. (2006b). Low temperature conditioning reduces postharvest chilling injury in loquat fruit. *Postharvest Biology and Technology*, 41(3), 252–259. <https://doi.org/10.1016/j.postharvbio.2006.04.015>
- Calvo, B. O., Parapugna, T. L., & Lagorio, M. G. (2017). Variability in chlorophyll fluorescence spectra of eggplant fruit grown under different light environments: A case study. *Photochemical and Photobiological Sciences*, 16(5), 711–720. <https://doi.org/10.1039/c6pp00475j>
- Cheng, X., Kondo, N., Ogawa, Y., Shiigi, T., Widodo, S., Watanabe, Y., & Fujiura, T. (2015). A halation reduction method for high quality images of tomato fruits in greenhouse. *Engineering in Agriculture, Environment and Food*, 8(4), 200–206. <https://doi.org/10.1016/j.eaef.2015.10.001>
- Choong, F. X., Bäck, M., Steiner, S. E., Melican, K., Nilsson, K. P. R., Edlund, U., & Richter-Dahlfors, A. (2016). Nondestructive, real-time determination and visualization of cellulose, hemicellulose and lignin by luminescent oligothiophenes. *Scientific Reports*, 6(1), Article 35578. <https://doi.org/10.1038/srep35578>
- Condurache, N.-N., Croitoru, C., Enachi, E., Bahrim, G.-E., Stănciuc, N., & Răpeanu, G. (2021). Eggplant peels as a valuable source of anthocyanins: Extraction, thermal stability and biological activities. *Plants*, 10(3), 577. <https://doi.org/10.3390/plants10030577>
- Díaz-Pérez, J. C. (1998). Transpiration rates in eggplant fruit as affected by fruit and calyx size. *Postharvest Biology and Technology*, 13(1), 45–49. [https://doi.org/10.1016/S0925-5214\(97\)00078-1](https://doi.org/10.1016/S0925-5214(97)00078-1)
- Doğan, M., Arslan, O., & Doğan, S. (2002). Substrate specificity, heat inactivation and inhibition of polyphenol oxidase from different aubergine cultivars. *International Journal of Food Science and Technology*, 37(4), 415–423. <https://doi.org/10.1046/j.1365-2621.2002.00580.x>
- Donaldson, L. (2020). Autofluorescence in plants. *Molecules*, 25(10), 2393. <https://doi.org/10.3390/molecules25102393>
- Drabant, R., Pliszka, B., & Olszewska, T. (1999). Fluorescence properties of plant anthocyanin pigments. I. Fluorescence of anthocyanins in *Brassica oleracea* L. extracts. *Journal of Photochemistry and Photobiology B: Biology*, 50(1), 53–58. [https://doi.org/10.1016/S1011-1344\(99\)00070-6](https://doi.org/10.1016/S1011-1344(99)00070-6)
- Drimbarean, A., & Whelan, P. F. (2001). Experiments in colour texture analysis. *Pattern Recognition Letters*, 22(10), 1161–1167. [https://doi.org/10.1016/S0167-8655\(01\)00058-7](https://doi.org/10.1016/S0167-8655(01)00058-7)
- Gajewski, M., & Arasimowicz, D. (2004). Sensory quality of eggplant fruits (*Solanum melongena* L.) as affected by cultivar and maturity stage. *Polish Journal of Food and Nutrition Sciences*, 54(3), 249–254.
- Gajewski, M., Katarzyna, K., & Bajer, M. (2009). The influence of postharvest storage on quality characteristics of fruit of eggplant cultivars. *Notulae Botanicae Horti Agrobotanici Cluj-Napoca*, 37(2), 200–205. <https://doi.org/10.15835/nbha3723184>
- Gidado, M. J., Gunny, A. A. N., Gopinath, S. C. B., Ali, A., Wongs-Aree, C., & Salleh, N. H. M. (2024). Challenges of postharvest water loss in fruits: Mechanisms, influencing factors, and effective control strategies – A comprehensive review. *Journal of Agriculture and Food Research*, 17, Article 101249. <https://doi.org/10.1016/j.jafr.2024.101249>
- Gonzalez, R. C., & Woods, R. E. (2018). *Digital image processing* (4th ed.). NY: Pearson/Prentice Hall.
- Grierson, W., & Wardowski, W. F. (1978). Relative humidity effects on the postharvest life of fruits and vegetables. *HortScience*, 13(5), 570–574. <https://doi.org/10.21273/HORTSCI.13.5.570>
- Gürbüz, N., Uluişik, S., Frary, A., Frary, A., & Doğanlar, S. (2018). Health benefits and bioactive compounds of eggplant. *Food Chemistry*, 268, 602–610. <https://doi.org/10.1016/j.foodchem.2018.06.093>
- Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3(6), 610–621. <https://doi.org/10.1109/TSMC.1973.4309314>
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). NY: Springer <https://link.springer.com/book/10.1007/978-0-387-84858-7>
- He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9), 1263–1284. <https://doi.org/10.1109/TKDE.2008.239>
- Humeau-Heurtier, A. (2022). Color texture analysis: A survey. *IEEE Access*, 10, 107993–108003. <https://doi.org/10.1109/ACCESS.2022.3213439>
- Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering*, 9(3), 90–95.
- Jha, S. N., Matsuoka, T., & Miyauchi, K. (2002). PH—Postharvest technology: Surface gloss and weight of eggplant during storage. *Biosystems Engineering*, 81(4), 407–412. <https://doi.org/10.1006/bioe.2002.0044>
- Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, 2, 1137–1145.
- Konagaya, K., Omwange, K. A., Riza, D. F. A., Khaliduzzaman, A., Oliver, A. M., Rovira-Más, F., Nagasato, H., Ninomiya, K., & Kondo, N. (2020). Association of fruit, pericarp, and epidermis traits with surface autofluorescence in green peppers. *Photochemical and Photobiological Sciences*, 19(12), 1630–1635. <https://doi.org/10.1039/d0pp00236d>
- Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). *Applied linear statistical models* (5th ed.). McGraw-Hill/Irwin.
- Ladokhin, A. S. (2006). Fluorescence spectroscopy in peptide and protein analysis. In *Encyclopedia of analytical chemistry*. John Wiley & Sons, Ltd. <https://doi.org/10.1002/9780470027318.a1611>
- Lawaetz, A. J., & Stedmon, C. A. (2009). Fluorescence intensity calibration using the Raman scatter peak of water. *Applied Spectroscopy*, 63(8), 936–940. <https://doi.org/10.1366/000370209788964548>
- Lichtenthaler, H. K. (2021). Multi-colour fluorescence imaging of photosynthetic activity and plant stress. *Photosynthetica*, 59(SPECIAL ISSUE), 364–380. <https://doi.org/10.32615/ps.2021.020>
- Lu, Y., Saeys, W., Kim, M., Peng, Y., & Lu, R. (2020). Hyperspectral imaging technology for quality and safety evaluation of horticultural products: A review and celebration of the past 20-year progress. *Postharvest Biology and Technology*, 170, Article 111318. <https://doi.org/10.1016/j.postharvbio.2020.111318>
- Mahajan, P. V., Oliveira, F. A. R., & Macedo, I. (2008). Effect of temperature and humidity on the transpiration rate of the whole mushrooms. *Journal of Food Engineering*, 84(2), 281–288. <https://doi.org/10.1016/j.jfoodeng.2007.05.021>
- McKinney, W. (2010). Data structures for statistical computing in python. In S. van der Walt, & J. Millman (Eds.), *Proceedings of the 9th python in science conference* (pp. 56–61). <https://doi.org/10.25080/Majora-92bf1922-00a>
- Momin, M. A., Kondo, N., Ogawa, Y., Ido, K., & Ninomiya, K. (2013). Patterns of fluorescence associated with citrus peel defects. *Engineering in Agriculture, Environment and Food*, 6(2), 54–60. [https://doi.org/10.1016/S1881-8366\(13\)80027-4](https://doi.org/10.1016/S1881-8366(13)80027-4)
- Monago-Maraña, O., Durán-Merás, I., Galeano-Díaz, T., & Muñoz de la Peña, A. (2016). Fluorescence properties of flavonoid compounds. Quantification in paprika samples using spectrofluorimetry coupled to second order chemometric tools. *Food Chemistry*, 196, 1058–1065. <https://doi.org/10.1016/j.foodchem.2015.10.041>
- Moretti, C. L., Mattos, L. M., Calbo, A. G., & Sargent, S. A. (2010). Climate changes and potential impacts on postharvest quality of fruit and vegetable crops: A review. *Food Research International*, 43(7), 1824–1832. <https://doi.org/10.1016/j.foodres.2009.10.013>
- Mulas, M., Lafuente, M. T., & Zacarias, L. (1996). Lignin and gum deposition in wounded 'Oroval' clementines as affected by chilling and peel water content. *Postharvest Biology and Technology*, 7(3), 243–251. [https://doi.org/10.1016/0925-5214\(95\)00036-4](https://doi.org/10.1016/0925-5214(95)00036-4)
- Muñoz, A., & González, J. (2010). Representing functional data using support vector machines. *Pattern Recognition Letters*, 31(6), 511–516. <https://doi.org/10.1016/j.patrec.2009.07.014>
- Nedbal, L., & Whitmarsh, J. (2004). Chlorophyll fluorescence imaging of leaves and fruits. In G. C. Papageorgiou & Govindjee (Eds.), *Chlorophyll a fluorescence: A signature of photosynthesis* (pp. 389–407). Netherlands: Springer. https://doi.org/10.1007/978-1-4020-3218-9_14
- Nie, S., Al Riza, D. F., Ogawa, Y., Suzuki, T., Kuramoto, M., Miyata, N., & Kondo, N. (2020). Potential of a double lighting imaging system for characterization of 'Hayward' kiwifruit harvest indices. *Postharvest Biology and Technology*, 162, Article 111113. <https://doi.org/10.1016/j.postharvbio.2019.111113>
- Nurulhuda, A., Riza, D. F. A., Muhariza, Kuramoto, M., Suzuki, T., & Kondo, N. (2021). Monitoring of fluorescence characteristic in tomato surface during over-ripening stage. *IOP Conference Series: Earth and Environmental Science*, 733(1), Article 012016. <https://doi.org/10.1088/1755-1315/733/1/012016>
- Padmanabhan, P., Cheema, A., & Paliyath, G. (2016). Solanaceous fruits including tomato, eggplant, and peppers. In B. Caballero, P. M. Finglas, & F. Toldrá (Eds.), *Encyclopedia of food and health* (pp. 24–32). Academic Press. <https://doi.org/10.1016/B978-0-12-384947-2.00696-6>

- Pandiselvam, R., Prithviraj, V., Manikantan, M. R., Kothakota, A., Rusu, A. V., Trif, M., & Mousavi Khaneghah, A. (2022). Recent advancements in NIR spectroscopy for assessing the quality and safety of horticultural products: A comprehensive review. *Frontiers in Nutrition*, 9, 973457. <https://doi.org/10.3389/fnut.2022.973457>
- Paull, R. E. (1999). Effect of temperature and relative humidity on fresh commodity quality. *Postharvest Biology and Technology*, 15(3), 263–277. [https://doi.org/10.1016/S0925-5214\(98\)00090-8](https://doi.org/10.1016/S0925-5214(98)00090-8)
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in python. *Journal of Machine Learning Research*, 12(85), 2825–2830.
- Rai, S., Singh, B. K., Bhartiya, P., Singh, A., Kumar, H., Dutta, P. K., & Mehrotra, G. K. (2017). Lignin derived reduced fluorescence carbon dots with theranostic approaches: Nano-drug-carrier and bioimaging. *Journal of Luminescence*, 190, 492–503. <https://doi.org/10.1016/j.jlumin.2017.06.008>
- Learning with kernels: Support vector machines, regularization, optimization, and beyond.* (2001). In Schölkopf, B., & Smola, A. J. (Eds.), (2001). The MIT Press. <https://doi.org/10.7551/mitpress/4175.003.0029>
- Seabold, S., & Perktold, J.. Statsmodels: Econometric and statistical modeling with Python. <https://doi.org/10.25080/Majora-92bf1922-011>.
- Stedmon, C., Markager, S., & Bro, R. (2003). Tracing dissolved organic matter in aquatic environments using a new approach to fluorescence spectroscopy. *Marine Chemistry*, 82, 239–254. [https://doi.org/10.1016/S0304-4203\(03\)00072-0](https://doi.org/10.1016/S0304-4203(03)00072-0)
- Stommel, J. R., & Whitaker, B. D. (2003). Phenolic acid content and composition of eggplant fruit in a germplasm core subset. *Journal of the American Society for Horticultural Science*, 128(5), 704–710. <https://doi.org/10.21273/JASHS.128.5.0704>
- Tan, L., Du, W., Zhang, Y., Tang, L.-J., Jiang, J.-H., & Yu, R.-Q. (2020). Rayleigh scattering correction for fluorescence spectroscopy analysis. *Chemometrics and Intelligent Laboratory Systems*, 203, Article 104028. <https://doi.org/10.1016/j.chemolab.2020.104028>
- Tsouvaltzis, P., Babellahi, F., Amodio, M. L., & Colelli, G. (2020). Early detection of eggplant fruit stored at chilling temperature using different non-destructive optical techniques and supervised classification algorithms. *Postharvest Biology and Technology*, 159, Article 111001. <https://doi.org/10.1016/j.postharvbio.2019.111001>
- Utku, H., & Köksel, H. (1998). Use of statistical filters in the classification of wheats by image analysis. *Journal of Food Engineering*, 36(4), 385–394. [10.1016/S0260-8774\(98\)00072-7](https://doi.org/10.1016/S0260-8774(98)00072-7)
- Vanholme, R., De Meester, B., Ralph, J., & Boerjan, W. (2019). Lignin biosynthesis and its integration into metabolism. *Current Opinion in Biotechnology*, 56, 230–239. <https://doi.org/10.1016/j.copbio.2019.02.018>
- Wright, H., DeLong, J., Lada, R., & Prange, R. (2009). The relationship between water status and chlorophyll a fluorescence in grapes (*Vitis* spp.). *Postharvest Biology and Technology*, 51(2), 193–199. <https://doi.org/10.1016/j.postharvbio.2008.07.004>
- Wulf, J. S., Geyer, M., Nicolai, B., & Zude, M. (2005). Non-destructive assessment of pigments in apple fruit and carrot by laser-induced fluorescence spectroscopy (LIFS) measured at different time-gate positions. *Acta Horticulturae*, 682, 1387–1394. <https://doi.org/10.17660/ActaHortic.2005.682.186>
- Xue, L., Liu, X., Lu, S., Cheng, G., Hu, Y., Liu, J., Dou, Z., Cheng, S., & Liu, G. (2021). China's food loss and waste embodies increasing environmental impacts. *Nature Food*, 2(7), 519–528. <https://doi.org/10.1038/s43016-021-00317-6>
- Zhu, N., Zhao, C., Wei, Y., Sun, C., Wu, D., & Chen, K. (2021). Biosynthetic labeling with 3-O-propargylcaffeoyl alcohol reveals in vivo cell-specific patterned lignification in loquat fruits during development and postharvest storage. *Horticulture Research*, 8 (1), 1–11. <https://doi.org/10.1038/s41438-021-00497-z>