Progress in Agricultural Engineering Sciences 21 (2025) 1, 377–391
DOI: 10.1556/446.2025.00220

Rapid assessment of egg freshness by handheld NIR spectrometer coupled with Random Forest algorithm

NGA THI THANH HA[1,3*], HOA XUAN MAC[1,3], THANH TUNG PHAM[1,4], LIEN LE PHUONG NGUYEN[1], LÁSZLÓ BARANYAI[1], LÁSZLÓ FERENC FRIEDRICH[1], ADRIENN TÓTH[1], CSABA NÉMETH[2] and QUANG DUC NGUYEN[1]

[1] Institute of Food Science and Technology, Hungarian University of Agriculture and Life Sciences, 1118 Budapest, Hungary

[2] Capriovus Ltd., 2317 Szigetcsép, Hungary

[3] Faculty of Food Science and Technology, Ho Chi Minh City University of Industry and Trade, Ho Chi Minh 700000, Vietnam

[4] Faculty of Chemical and Food Technology, Ho Chi Minh City University of Technology and Education, Ho Chi Minh 700000, Vietnam

ORIGINAL RESEARCH PAPER

Received: June 18, 2025 • Accepted: October 1, 2025
Published online: October 18, 2025

ABSTRACT

This study evaluated the potential of a handheld near-infrared (NIR) spectrometer for rapid estimation of freshness of egg. Random Forest (RF) and Partial Least Squares (PLS) models were compared for Regression (R) and Classification (C) using various spectral pre-processing methods such as Savitzky-Golay smoothing (SGS), multiplicative scatter correction (MSC), first derivative (1D), and second derivative (2D). Pre-processing the spectra with multiplicative scatter correction (MSC) yielded the best results. RF-R outperformed PLS-R for predicting Haugh unit. MSC-RF-R with selected wavelengths showed a slight reduction in performance but offered an eight-fold decrease in computational time compared to full-spectrum model. Balancing accuracy and efficiency, MSC-RF-R based on selected wavelengths

* Corresponding author. E-mail: ngahtt@huit.edu.vn

(R^2 = 0.943, RMSE = 2.600) is recommended. For classifying eggs based on storage time, MSC-RF-C achieved higher performance (F1-score = 99.31%) than MSC-PLS-DA (F1-score = 95.90%). In classifying eggs by grade, MSC-RF-C (F1-score = 98.75%) performed comparably to MSC-PLS-DA (F1-score = 98.83%). These findings demonstrate that handheld NIR spectrometer combined with RF models is an effective tool for assessing egg freshness.

KEYWORDS

egg freshness, egg quality, Haugh unit, Random Forest, spectral pre-processing

1. INTRODUCTION

Hen eggs are popular nutrient source in the human diet due to their affordability and essential amino acids (Pham et al., 2024). According to the statistical data, in 2024 the hen egg is consumed with the average volume per person expected to be 6.2 kg (Statista, 2024). However, egg quality degrades quickly after laying (Cruz-Tirado et al., 2021). Egg freshness decline is primarily due to moisture and carbon dioxide loss through the shell, which leads to weight reduction and increased albumen pH (Liu et al., 2016). This change weakens the protein network, reducing the viscosity and height of the albumen (Giunchi et al., 2008). Egg quality deterioration does not only threaten consumer health, but also causes economic loss across the supply chain due to reduced shelf-life and potential product rejection (Yao et al., 2024). Therefore, monitoring egg quality during storage is essential to ensure that only safe and wholesome eggs reach consumers.

The standard metric for assessing egg freshness is the Haugh Unit (HU), which is based on the relationship between egg weight and albumen height (Haugh, 1937). Eggs are classified into quality grades ("AA", "A", "B", and "C"), but only "AA" and "A" are commercially acceptable (USDA, 2000). Despite its widespread use, HU determination is destructive, laboratorial intensive, and not suitable for large-scale or real-time quality control.

Near-infrared (NIR) spectroscopy has emerged as a promising non-destructive, rapid, and accurate technique for food quality assessment. NIR light (700–1,900 nm) penetrates up to 4 mm into biological materials (Lammertyn et al., 2000), and provides molecular information by detecting overtone and combination bands of C–H, O–H, and N–H bonds, which are commonly found in egg proteins and water (Karoui et al., 2006). Recently, handheld NIR devices have gained traction in the food industry due to their portability, affordability, and suitability for *in situ* analysis (Cruz-Tirado et al., 2021; Yao et al., 2024). Nevertheless, the number of studies employing handheld NIR spectrometers to monitor egg quality is quite limited.

Traditional multivariate methods for spectral calibration, such as partial least squares discriminant analysis (PLS-DA) and partial least squares regression (PLS-R), are well-suited for linear behavior of data (Loffredi et al., 2021). However, the HU reflects complex, potentially nonlinear biochemical changes, requiring more sophisticated approaches. Algorithms like support vector machines (SVM) and artificial neural networks (ANN) have demonstrated effectiveness in handling nonlinear spectral data (Cruz-Tirado et al., 2021; Lin et al., 2011; Puertas et al., 2023; Zhao et al., 2010). Nevertheless, SVM performance is highly dependent on the selection of kernel functions and lacks the feature selection ability. Additionally, ANN model training is often time-consuming. In contrast, Random Forest (RF), a non-parametric, ensemble-based method, offers advantages in both classification and regression, supports feature selection, and generally exhibits faster training times compared to ANN (Qiu et al., 2015). Moreover, RF is particularly effective when training data are limited (Ramezan et al., 2021). However, the application of RF in egg quality assessment using NIR data has yet to be fully explored.

This study aims to evaluate the feasibility of using a handheld NIR spectrometer combined with the RF algorithm to monitor egg freshness during storage. The NIR spectra were pre-treated by various pre-processing methods in combination with RF algorithm for qualitatively and quantitatively analysing egg's internal quality. Additionally, conventional models, partial least squares discriminant analysis (PLS-DA) and partial least squares regression (PLS-R), were employed for comparison with the RF algorithm.

2. MATERIALS AND METHODS

2.1. Preparation of egg sample

A total of 150 freshly laid brown shell hen eggs (size L: 65.05 ± 2.14 g) were obtained from Capriovus Ltd. (Szigetcsép, Hungary). Thirty eggs were randomly selected for the initial quality evaluation. The remaining 120 eggs were stored under room conditions (25 ± 2 °C; 68 ± 2% relative humidity) for up to four weeks to induce internal quality degradation. These storage conditions were selected in accordance with European Council Regulation No 589/2008, which does not mandate refrigeration for shell eggs (Council, 2008). A storage period of 4 weeks was long enough to facilitate the evaluation of egg freshness (Karoui et al., 2006). Each week, 30 eggs were randomly sampled for quality assessment, following the procedure illustrated in Fig. 1.

2.2. Determination of egg freshness

HU was used as the reference indicator of egg freshness. Each egg was weighed using a digital electronic scale (Kern PFB, Kern & Sohn GmbH, Balingen-Frommern, Germany), then broken onto a flat surface, and the height of albumen (mm) was measured at three different points (approximately 10 mm from the yolk) using a digital calliper (CD-20B, Mitutoyo, Kanagawa, Japan). HU was calculated using Equation (1) (Haugh, 1937), where H is the albumen height (mm) and W_f is the egg weight (g).

$$\mathrm{HU} = 100\log\left(H - 1.7W_f^{.37} + 7.57\right) \tag{1}$$

2.3. Acquisition of NIR spectra

Spectra were acquired using a handheld NIR spectrometer (Model NIR-S-G1, InnoSpectra) in reflectance mode at 25 ± 2 °C and 68 ± 2% RH. Eggs were positioned on the top of the optical window of the instrument, and spectra from three points around the middle of the eggshell were collected, yielding three spectra per egg. The scanning was performed in the middle of the eggshell to facilitate the examination of internal quality changes (Lin et al., 2011). The measurement was conducted in the wavelength range of 900–1,700 nm, resulting in 228 variables.

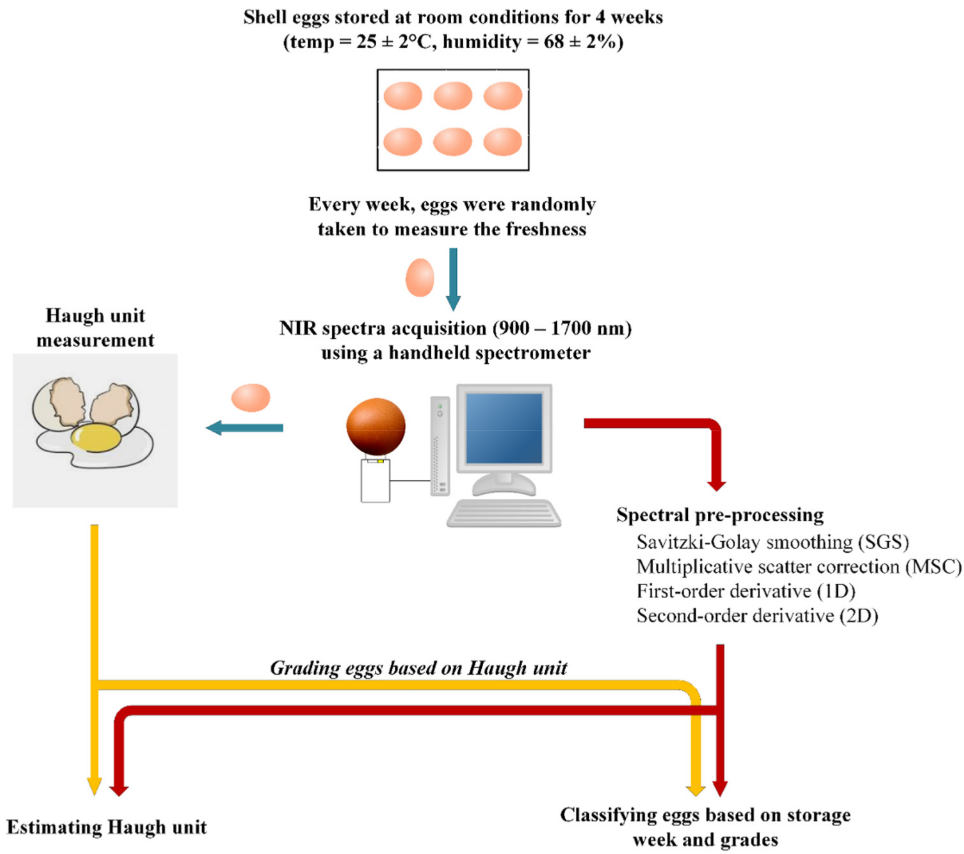


Fig. 1. Measurement procedure for egg quality

2.4. Statistical analysis

In this work, the processes of statistical analysis were performed using R (version 4.2.1) and RStudio (version 2023.06.1 + 524).

2.4.1. Analysis of variance (ANOVA). One-way ANOVA was conducted to assess changes in HU across storage periods. Tukey's post hoc test was used to determine significant pairwise differences between weeks. A significance level of 0.05 was generally applied for the analyses.

2.4.2. Spectral pre-processing and model development. Spectral pre-processing was performed to improve the quality and interpretability of spectral data before modelling. Four spectral pre-processing methods were tested: Savitzky-Golay smoothing (SGS), multiplicative scatter correction (MSC), first derivative (1D), and second derivative (2D).

Model development and evaluation followed the procedure outlined in Fig. 2. From each group of storage weeks (30 eggs), data from 24 eggs were randomly selected to form a training

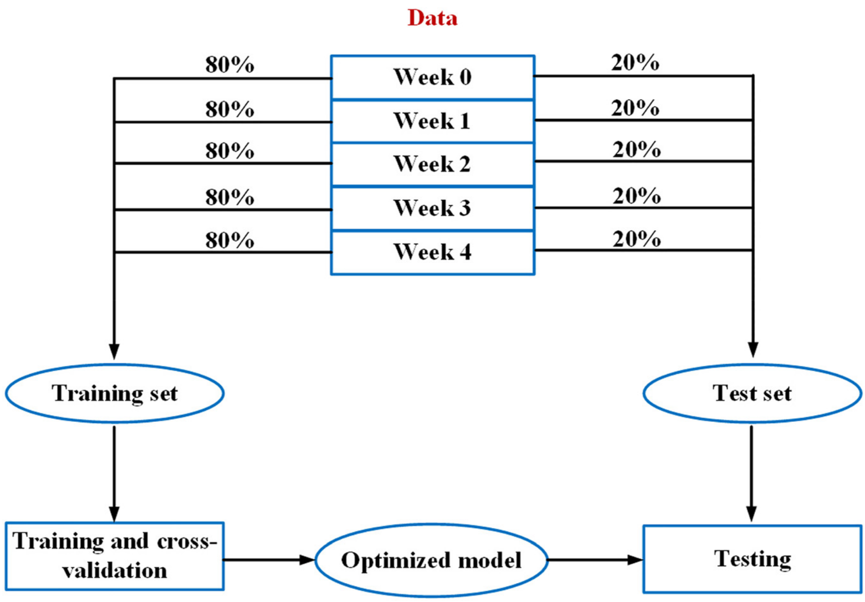


Fig. 2. Method of model development and validation

set, which accounted for 80% of dataset. The remaining 20% of dataset (from 6 eggs) was used to create a test set for externally testing the trained models. In the training step, models were trained and validated through 10-fold cross-validation. During cross-validation, model hyperparameters were tuned, and the optimal hyperparameters were selected at the maximum prediction accuracy.

For classification tasks, Random Forest Classification (RF-C) and Partial Least Squares Discrimination Analysis (PLS-DA) models were evaluated for classifying eggs according to their storage week and quality grade based on the HU. Overall accuracy and F1-score were used to test the model performance. Especially, F1-score is useful when the classes are imbalanced. An excellent classification should obtain an F1-score close to 100%. For regression, Random Forest Regression (RF-R) and Partial Least Squares Regression (PLS-R) models were assessed to estimate the HU. The coefficient of determination (R^2), root mean square error (RMSE), and the ratio of performance to deviation (RPD) were utilized to evaluate the model quality. A regression model with excellent performance should have RPD $\geq$2.0 (Reda et al., 2023). The hyperparameters of RF and PLS models were the number of randomly selected variables (mtry) and the number of latent variables (LV), respectively.

The *caret* package was used for modelling and validation (Kuhn, 2008). The *train()* function was developed and used to train the model. The function *trainControl()* was utilized to define the resampling method for model training. The function *varImp()* was employed to calculate the importance of each feature in the trained model based on its influence on the model predictions.

3. RESULTS AND DISCUSSIONS

3.1. Changes in egg freshness during storage based on HU

The decline obtained in HU over the 4-week storage period under ambient conditions (25 ± 2 °C) is illustrated in Fig. 3. ANOVA revealed a statistically significant decrease in HU across storage time ($F = 287.24$, $P < 0.001$). Tukey's post hoc test ($P < 0.05$) confirmed that each week exhibited significantly lower HU compared to the previous week. Freshly laid eggs initially exhibited grade AA quality (HU ≥ 72). After one week, eggs retained grade A quality (HU = 61–71), which is still acceptable for commercial sale (USDA, 2000). From week 2 onward, HU values dropped below 60 (grade B), indicating loss of freshness and unsuitability for retail. This trend aligns with earlier reports (Akyurek and Okur, 2009).

As shown in Fig. 4, the albumen of the fresh egg (week 0) maintained a firm, two-layer structure with a well-defined boundary, whereas after four weeks, the albumen became more fluid and spread significantly. The decline in egg freshness during storage is primarily attributed to the breakdown of carbonic acid within the albumen, which releases carbon dioxide and water. As the carbon dioxide and water evaporate through the eggshell, the egg loses weight, and the texture of the albumen changes (Karoui et al., 2006). Additionally, the interaction between ovomucin and lysozyme weakens the albumen layer (Stadelman et al., 2017). These changes ultimately result in decreased egg freshness, as reflected by reduced HU values.

3.2. Qualitative analysis of egg freshness using NIR spectra

The ability of the proposed technique to qualitatively assess egg freshness was assessed by classifying eggs according to storage time and egg grade. Four pre-processing techniques (SGS, MSC, 1D, and 2D) were evaluated (Fig. 5). The classification results using full spectra

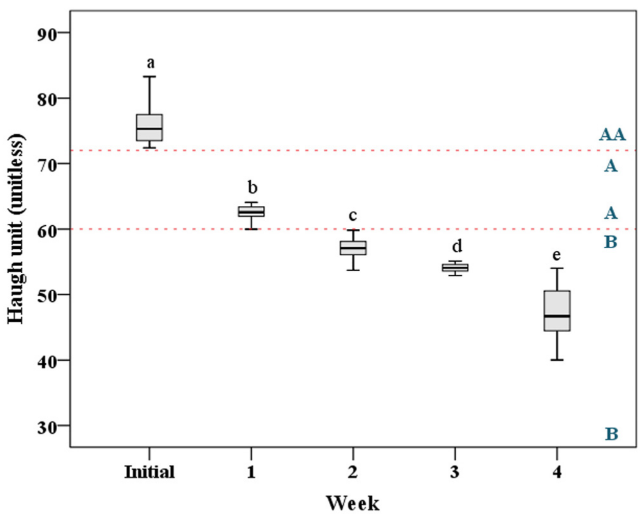
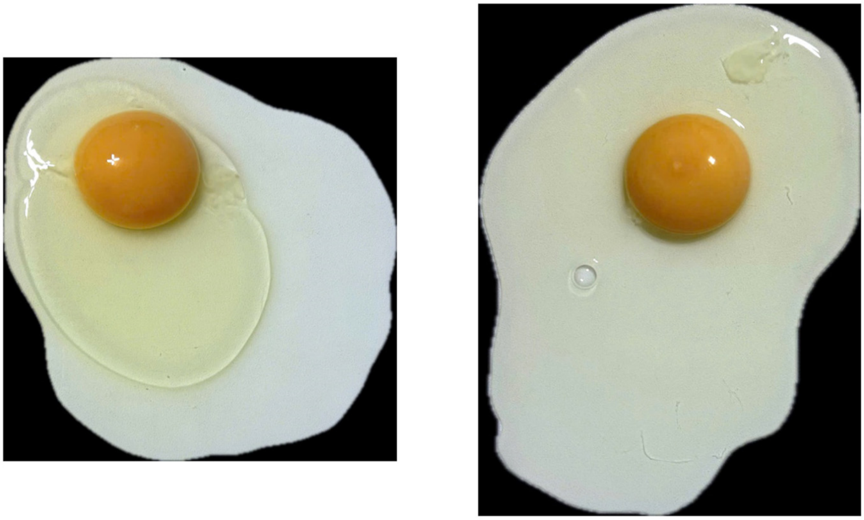


Fig. 3. Changes in Haugh Unit (HU) during storage. Different lowercase letters (a–e) indicate statistical significance based on Tukey's test at P-value <0.05. AA, A, and B stand for egg quality grades based on HU



Week 0 (Initial) Week 4

Fig. 4. Egg samples taken at week 0 (initial) and week 4

with different pre-processing techniques are presented in Tables 1 and 2. Overall, the RF-C and PLS-DA models demonstrated good generalization, with closely aligned training and testing performances. All models achieved average F1-scores above 80%, indicating that both RF-C and PLS-DA were effective in discriminating egg samples.

For classification based on storage time, the F1-score showed an increasing trend and reached the highest value (100%) by week 4 for both RF-C and PLS-DA. This improvement in classification accuracy can be attributed to the more significant degradation of egg freshness over time, which was confirmed by the results of ANOVA and Tukey's test in the previous section. For PLS-DA, only MSC pre-processing improved accuracy relative to raw spectra. For RF-C, all pre-processed spectra provided better classification results than raw data, except for the 2D pre-processing method. MSC-RF-C achieved the highest performance, with an average F1-score of 99.31%, outperforming MSC-PLS-DA (95.90%). These findings suggest that NIR spectroscopy combined with RF-C is highly effective for recognizing eggs based on storage time.

When considering classification according to egg grade, the use of 2D pre-processing resulted in a decrease in model performance for both RF-C and PLS-DA, likely due to noise amplification (Fig. 5d). For PLS-DA, there were no significant differences in classification performance between raw, SGS, MSC, and 1D spectra. For RF-C, MSC produced the best results, followed by SGS, 1D, raw spectra, and 2D. These observations imply that the performance of RF models is more influenced by the spectral pre-treatment method than by the PLS-DA model. Among pre-processing methods, RF-C models generally underperformed relative to PLS-DA models, except for MSC-RF-C. Based on average F1-score, MSC-RF-C (98.75%) showed comparable performance to PLS-DA models using raw, SGS, MSC, and 1D spectra (98.06–98.98%). Overall, the proposed technique is effective for distinguishing eggs based on their grades.

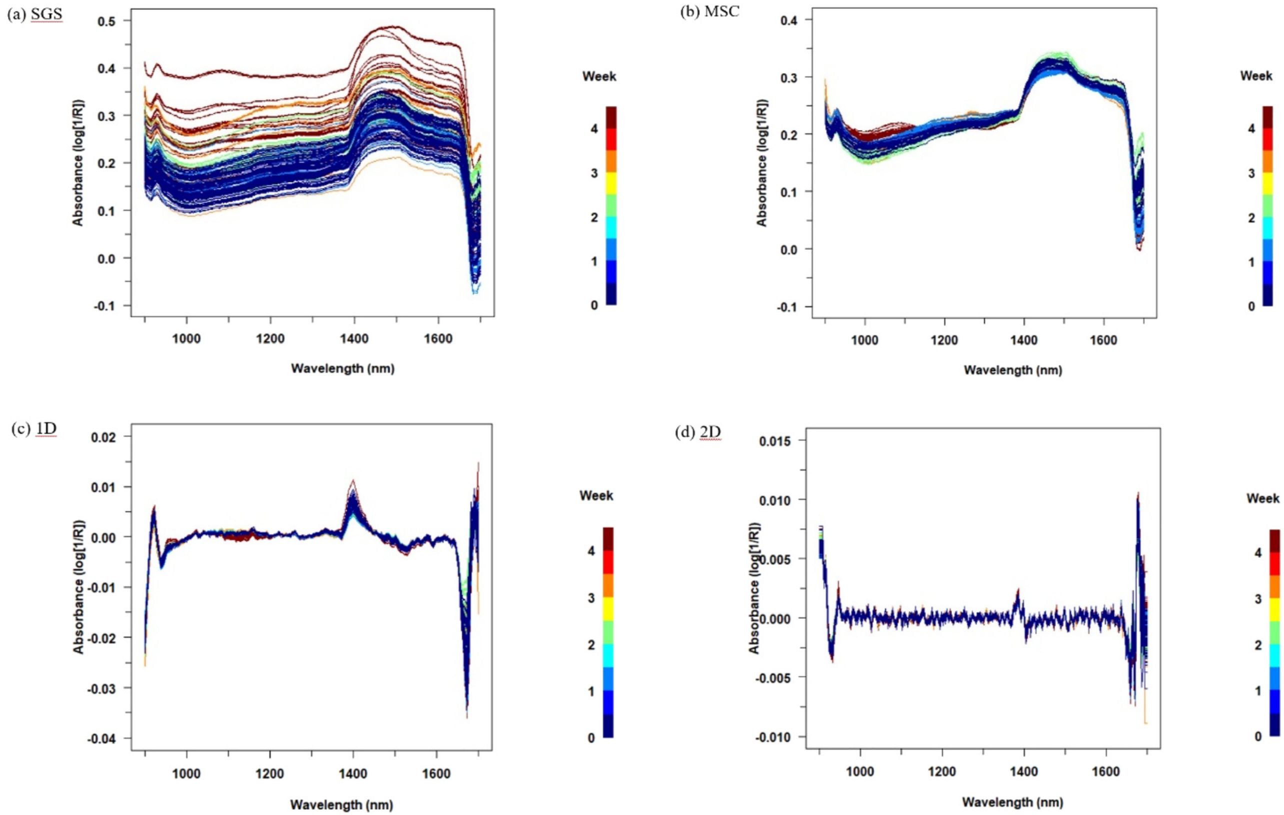


Fig. 5. NIR spectra pre-processed by (a) Savitzky-Golay smoothing (SGS), (b) multiplicative scatter correction (MSC), (c) first derivative (1D), and (d) second derivative (2D)

Table 1. Classification result of eggs based on storage time

Model	Pre-processing	Training: Hyper-parameter	Training: Overall accuracy (%)	Testing: Overall accuracy (%)	Testing: F1-score per storage week (%) Initial	Week 1	Week 2	Week 3	Week 4	Testing: Average F1-score (%)
PLS-DA	Raw	LV = 20	94.51	94.26	86.27	85.71	100	100	100	94.40
	SGS	LV = 22	94.50	94.30	85.71	86.27	100	97.67	100	93.93
	MSC	LV = 19	95.17	95.90	98.04	93.10	88.37	100	100	95.90
	1D	LV = 16	93.79	93.44	97.50	82.93	81.08	100	100	92.30
	2D	LV = 25	82.81	82.79	86.11	96.15	61.54	59.46	100	80.65
RF-C	Raw	mtry = 2	96.76	96.72	95.12	97.14	94.74	97.78	100	96.96
	SGS	mtry = 2	97.06	97.54	95.77	95.45	97.56	100	100	97.76
	MSC	mtry = 2	98.65	99.18	98.46	98.11	100	100	100	99.31
	1D	mtry = 2	97.03	98.36	95.45	95.24	100	100	100	98.14
	2D	mtry = 2	84.72	84.43	85.71	89.80	76.00	68.42	100	83.99

Table 2. Results of classification of eggs based on quality grades

Model	Pre-processing	Training		Testing				
		Hyper-parameter	Overall accuracy (%)	Overall accuracy (%)	F1-score per egg grade (%)			Average F1-score (%)
					AA	A	B	
PLS-DA	Raw	LV = 14	100	99.18	98.46	97.85	98.26	98.06
	SGS	LV = 14	99.21	100	100	98.21	99.75	98.98
	MSC	LV = 19	99.15	98.54	98.18	99.15	99.16	98.83
	1D	LV = 13	99.10	98.91	98.46	98.45	99.26	98.86
	2D	LV = 15	95.18	92.62	84.75	91.67	96.35	94.01
RF-C	Raw	mtry = 2	97.32	96.72	96.88	91.30	98.51	95.56
	SGS	mtry = 65	97.05	97.54	95.38	100	97.78	97.72
	MSC	mtry = 2	98.92	99.18	98.46	97.78	100	98.75
	1D	mtry = 2	97.93	96.72	93.55	100	97.10	96.88
	2D	mtry = 65	90.64	92.62	87.50	93.02	94.89	91.80

3.3. Estimation of HU

Accurate prediction of the HU is crucial for quantifying egg freshness. In this study, regression models were developed using PLS-R and RF-R algorithms, combined with various spectral pre-processing techniques.

Among all pre-processing methods, models generalized well, as R^2 values were approximately equal between training and testing for both PLS-R and RF-R (Table 3). All models achieved RPD values above 2.0, indicating excellent predictive performance, excepting such model based on 2D pre-processed data (RPD = 1.63–1.70). The underperformance of models using 2D data is likely due to excessive noise amplification (Fig. 5d). For PLS-R, enhanced performance was observed only with SGS, while other pre-processing methods reduced model quality compared to raw spectra. For RF-R, improved accuracy was achieved for MSC, while other techniques showed lower performances than raw data. When comparing the two

Table 3. Performance of regression models combined with different pre-processing techniques

Model	Pre-processing	Training			Testing		
		Hyper-parameter	R^2	RMSE	R^2	RMSE	RPD
PLS-R	Raw	LV = 16	0.884	3.784	0.876	3.645	2.83
	SGS	LV = 15	0.892	3.620	0.891	3.700	2.97
	MSC	LV = 13	0.843	4.400	0.848	4.227	2.47
	1D	LV = 12	0.868	3.853	0.873	4.046	2.82
	2D	LV = 7	0.681	6.430	0.678	6.415	1.63
RF-R	Raw	mtry = 65	0.927	2.934	0.925	2.978	3.61
	SGS	mtry = 129	0.928	2.948	0.923	2.986	3.60
	MSC	mtry = 2	0.963	2.161	0.964	2.224	4.80
	1D	mtry = 65	0.915	3.289	0.891	3.568	3.00
	2D	mtry = 65	0.729	6.078	0.682	6.403	1.70

regression methods, RF-R consistently outperformed PLS-R across all investigated pre-processing approaches. Using full spectra (228 wavelengths), the MSC-RF-R model achieved the highest predictive accuracy for the test set, with R^2 = 0.964, RMSE = 2.224 and RPD = 4.80 (Fig. 7a), respectively.

To reduce model complexity and computation time, the most relevant wavelengths were selected based on the MSC-RF-R model using full spectra. This selection process identified the wavelengths that contributed the most to the model (Fig. 6). Among these, seven wavelengths (1,386, 1,027, 1,044, 1,379, 1,003, 1,388, and 1,099 nm) were particularly significant, with importance values exceeding 80%. These wavelengths corresponded to key spectral variations observed with storage time. Notably, the bands around 1,440 nm are linked to moisture transfer process through the shell pores (Osborne et al., 1993), caused by the release of carbon dioxide and water from the breakdown of carbonic acid within the albumen (Karoui et al., 2006). Additionally, the wavelengths near 1,020 nm correspond to structural changes in protein, likely caused by the degradation of the ovomucin complex (Cruz-Tirado et al., 2021) and the conversion of ovalbumin to S-ovalbumin during storage (Huang et al., 2012).

A threshold of 60% relative importance was applied to select the most impactful variables for developing a simplified RF-R model. As a result, MSC-RF-R model with selected variables performed well on the test set, with an RPD of 4.13 (Fig. 7b). The MSC-RF-R model using selected variables slightly underperformed compared with the full-spectrum model (RPD = 4.80), but achieved a nearly eightfold reduction in computation time (from 290 to 35 s) on a standard personal laptop (11th Gen Intel® Core™ i3-1115G4 CPU @ 3.00 GHz, 4 cores, 8 GB RAM, Windows 10 operating system). Thus, spectral simplification through variable selection preserved model robustness while greatly improving computational efficiency. Balancing accuracy and efficiency, the MSC-RF-R model with selected wavelengths is recommended for HU quantification in this study.

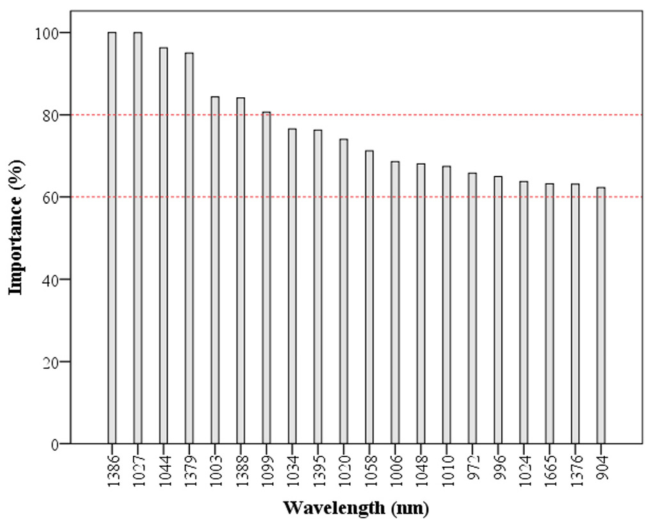


Fig. 6. The most important wavelengths selected from MSC spectra by RF-R model

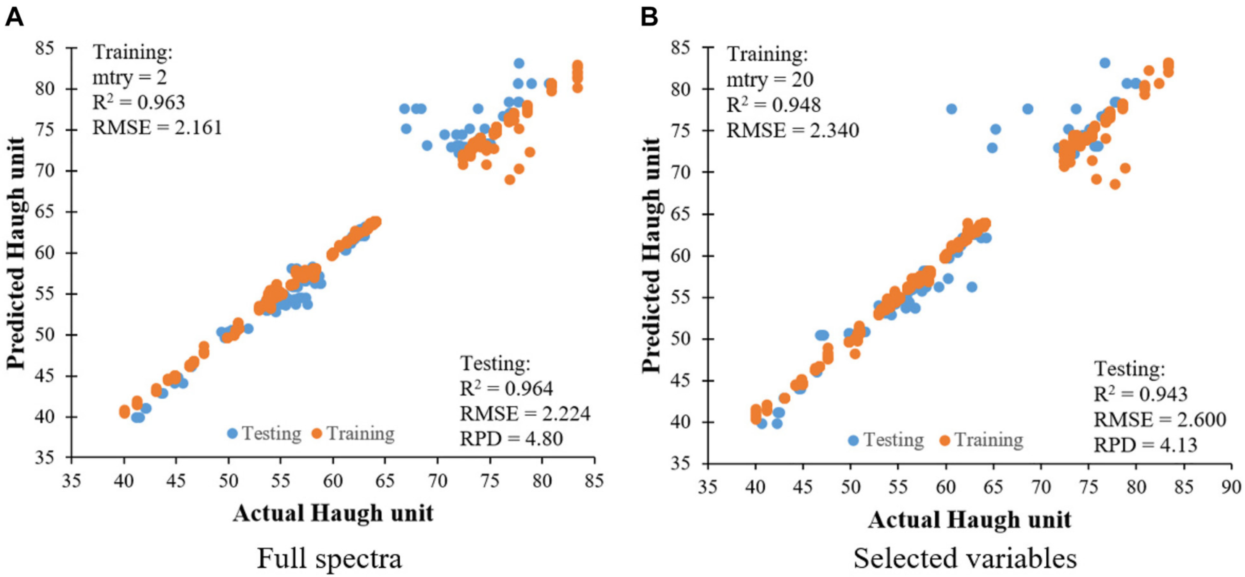


Fig. 7. Performance of MSC-RF-R models using full spectra and selected variables

Previous studies have employed both benchtop and portable spectrometers to analyse the egg freshness. Zhao et al. (2010) applied NIR spectroscopy benchtop device (1,000–2,500 nm) combined with support vector data description (SVDD) to distinguish fresh from stale eggs, achieving an accuracy of 93.3%. Lin et al. (2011) used NIR spectra (1,000–2,500 nm) and artificial neural network combined with genetic algorithms (GA-ANN) to predict Haugh Unit, reporting an R of 0.879 and RMSE of 2.443 (Lin et al., 2011), respectively. In the case of portable instruments, Cruz-Tirado et al. (2021) employed a portable NIR spectrometer (900–1,700 nm) with support vector machine (SVM) for egg quality prediction, achieving classification accuracies of 80.6–85.7% and regression performance with R^2_p of 0.77–0.84, RMSEP of 4.72–5.68, and RPD of 2.12–2.56. More recently, Yao et al. (2024) applied NIR spectra (912–1,690 nm) with convolutional neural network (CNN) to evaluate egg freshness, achieving classification accuracy of 90.7% and regression results of $R^2_P = 0.9059$, $RMSE_P = 4.8153$, RPD = 3.1201, respectively. Overall, the results obtained in the present study outperform those reported in previous research.

4. CONCLUSIONS

This study demonstrated the applicability of a handheld NIR spectrometer combined with RF algorithm for non-destructively analysing egg internal quality. Among the tested pre-processing techniques, MSC consistently improved model performance. For classification based on storage time, RF-C outperformed PLS-DA across all pre-processing approaches. In classifying eggs by grade, RF-C generally exhibited lower performance than PLS-DA, except for MSC-RF-C, which achieved comparable accuracy. In quantitative analysis, RF-R exhibited higher predictive accuracy than PLS-R in estimating HU values. Compared with the full-spectrum model, MSC-RF-R using selected wavelengths slightly reduced prediction accuracy but significantly improved computational efficiency, making it better suited for real-time applications. Overall, combining a handheld NIR spectrometer with RF algorithm provides a fast, accurate, and non-destructive approach for assessing egg freshness. The proposed technique can potentially be applied for on-site quality control in egg production and supply chains. The study was limited by a small sample size and the inclusion of only a single egg size and variety. Therefore, future work should explore the method across multiple egg sizes, varieties, and larger sample sizes to enhance its practical implementation.

ACKNOWLEDGEMENT

This work was supported by NRDIO Project No. 2023-1.1.1-PIACI_FÓKUSZ-2024-00035 and TKP2021-NVA-0022 as well as Flagship Research Groups Programme and Doctoral School of Food Science, MATE.

REFERENCES

Akyurek, H. and Okur, A.A. (2009). Effect of storage time, temperature and hen age on egg quality in free-range layer hens. *Journal of Animal and Veterinary Advances*, 8(10): 1953–1958.

Council, E. (2008). Commission Regulation (EC) No 589/2008 of 23 June 2008 laying down detailed rules for implementing Council Regulation (EC) No 1234/2007 as regards marketing standards for eggs, Available at: http://data.europa.eu/eli/reg/2008/589/2017-11-25 (Accessed: 15 September 2024).

Cruz-Tirado, J., da Silva Medeiros, M.L., and Barbin, D.F. (2021). On-line monitoring of egg freshness using a portable NIR spectrometer in tandem with machine learning. *Journal of food Engineering,* 306: 110643, https://doi.org/10.1016/j.jfoodeng.2021.110643

Giunchi, A., Berardinelli, A., Ragni, L., Fabbri, A., and Silaghi, F.A. (2008). Non-destructive freshness assessment of shell eggs using FT-NIR spectroscopy. *Journal of food Engineering*, 89(2): 142–148.

Haugh, R. (1937). The Haugh unit for measuring egg quality. *United States Egg Poultry, What Magazine*, 43: 522–555.

Huang, Q., Qiu, N., Ma, M., Jin, Y., Yang, H., Geng, F., and Sun, S. (2012). Estimation of egg freshness using S-ovalbumin as an indicator. *Poultry Science,* 91(3): 739–743, https://doi.org/10.3382/ps.2011-01639

Karoui, R., Kemps, B., Bamelis, F., De Ketelaere, B., Decuypere, E., and De Baerdemaeker, J. (2006). Methods to evaluate egg freshness in research and industry: a review. *European Food Research and Technology*, 222(5): 727–732.

Kuhn, M. (2008). Building predictive models in R using the caret package. *Journal of Statistical Software,* 28: 1–26, https://doi.org/10.18637/jss.v028.i05

Lammertyn, J., Peirs, A., De Baerdemaeker, J., and Nicolaı, B. (2000). Light penetration properties of NIR radiation in fruit with respect to non-destructive quality assessment. *Postharvest Biology and Technology*, 18(2): 121–132.

Lin, H., Zhao, J., Sun, L., Chen, Q., and Zhou, F. (2011). Freshness measurement of eggs using near infrared (NIR) spectroscopy and multivariate data analysis. *Innovative Food Science & Emerging Technologies*, 12(2): 182–186.

Liu, Y.-C., Chen, T.-H., Wu, Y.-C., Lee, Y.-C., and Tan, F.-J. (2016). Effects of egg washing and storage temperature on the quality of eggshell cuticle and eggs. *Food Chemistry*, 211: 687–693.

Loffredi, E., Grassi, S., and Alamprese, C. (2021). Spectroscopic approaches for non-destructive shell egg quality and freshness evaluation: opportunities and challenges. *Food Control*, 129: 108255.

Osborne, B.G., Fearn, T., and Hindle, P.H. (1993). *Practical NIR spectroscopy with applications in food and beverage analysis*.

Pham, T.T., Nguyen, L.L.P., Baranyai, L., Dam, M.S., Ha, N.T.T., Varga-Tóth, A., and FriedrichL.F. (2024). Evaluation of gel coating performance in extending the shelf life of egg: the role of surface area and initial weight. *Gels (2310-2861)*, 10(8).

Puertas, G., Cazón, P., and Vázquez, M. (2023). A quick method for fraud detection in egg labels based on egg centrifugation plasma. *Food Chemistry*, 402: 134507.

Qiu, S., Wang, J., Tang, C., and Du, D. (2015). Comparison of ELM, RF, and SVM on E-nose and E-tongue to trace the quality status of mandarin (Citrus unshiu Marc.). *Journal of Food Engineering*, 166: 193–203.

Ramezan, C.A., Warner, T.A., Maxwell, A.E., and Price, B.S. (2021). Effects of training set size on supervised machine-learning land-cover classification of large-area high-resolution remotely sensed data. *Remote Sensing,* 13(3): 368, https://doi.org/10.3390/rs13030368

Reda, R., Saffaj, T., Bouzida, I., Saidi, O., Belgrir, M., and Lakssir, B. (2023). Optimized variable selection and machine learning models for olive oil quality assessment using portable near infrared spectroscopy. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy,* 303: 123213, https://doi.org/10.1016/j.saa.2023.123213

Stadelman, W.J., Newkirk, D., and Newby, L. (2017). *Egg science and technology*. CRC Press.

Statista. (2024). Eggs - worldwide, Available at: https://www.statista.com/outlook/cmo/food/dairy-products-eggs/eggs/worldwide (Accessed: 20 September 2024).

USDA. (2000). Egg-grading manual. (Accessed: 15 September 2024).

Yao, K., Sun, J., Zhang, B., Du, X., and Chen, C. (2024). On-line monitoring of egg freshness using a portable NIR spectrometer combined with deep learning algorithm. *Infrared Physics & Technology*, 138: 105207.

Zhao, J., Lin, H., Chen, Q., Huang, X., Sun, Z., and Zhou, F. (2010). Identification of egg's freshness using NIR and support vector data description. *Journal of Food Engineering,* 98(4): 408–414, https://doi.org/10.1016/j.jfoodeng.2010.01.018