INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue X, October 2025

Detection of Free-Range Chicken Egg Freshness using a Portable Near-Infrared Spectrometer at Different Egg Orientations

Dharell B. Siano, Abigail G. Abuan, Carla I. Bautista

Bataan Peninsula State University

DOI: https://doi.org/10.51583/IJLTEMAS.2025.1410000145

Received: 02 November 2025; Accepted: 10 November 2025; Published: 24 November 2025

Abstract - Egg quality in terms of freshness for unfertilized free range chicken eggs was investigated in the study using a portable near-infrared spectrometer operating at 900 nm to 1700 nm. The egg freshness is commonly quantified based on the Haugh unit which is time consuming and destructive. Near-infrared spectroscopy can be used to assess the quality of eggs at the various stages of the supply chain. The portable near infrared spectrometer operating in reflectance mode was used to scan the egg sample in vertical and horizontal position.

The result showed that the highest classification accuracy was from the free-range chicken egg obtained from the BPSU farm with a cross-validation accuracy of 68.20% and a test accuracy of 63.60 %. Position 1 (vertical) gives the highest accuracy and it is attributed to the changes in air cell height during ageing which affects the spectral data obtained from the egg samples. The spectra were pretreated using Savitzky Golay 1st derivative with a smoothing point =7 and analyzed using stepwise discriminant analysis. The result showed the potential of the portable near infrared spectrometer to predict the freshness of free-range chicken egg real time. It can be implemented in online grading and can be a nondestructive technique for detecting egg freshness.

Keywords: spectrometer, freshness, free range, haugh unit, near-infrared spectroscopy

I. Introduction

Eggs are among the most widely consumed food items globally, with increasing attention due to their high nutritional value and affordability (Xie et al., 2023). Egg is a nutritious food product containing protein, fat, vitamins, and minerals (English, 2021) and it is considered as a staple food in the Philippines. In the context of egg production, the livestock sector includes the rearing of free-range poultry. Free-range chickens are those raised in a confined environment while allowing the birds to have access to vegetation and sunlight (PNS/BAFS 262:2018). The egg quality is affected by rearing, humidity, temperature, storage, handling, and egg age (Chambers et al., 2017). Freshness of egg is a major concern for the consumers. A decline in egg freshness is prominent as affected by prolonged storage time and its storage conditions (Akowuah, et al., 2020). A stale egg sold in the market can affect consumers' satisfaction. The egg freshness can be indicated by Haugh units (HU), air cell and weight loss (Grashorn, 2016).

The traditional method of determining HU are destructive method wherein it cannot be used in sorting of eggs because it is normally done in a single sample pick at a sample population. Various nondestructive techniques can be used in determining egg freshness such as near-infrared spectroscopy, hyperspectral imaging, Raman spectroscopy, acoustic response, dynamic weighing, and image descriptors (Yuan et al., 2023).

In this current study, a portable near infrared spectrometer in reflectance mode working at the near-infrared region (900 nm to 1700 nm) was used to determine the egg freshness in relation to theHaugh unit. Several studies used near-infrared spectroscopy in determining egg freshness that works in the visible or lower wavelength region. The study of Yuan et al., (2023) used brown eggs and acquired spectra at 550 – 980 nm and analyzed it using iPLS lasso selection resulting in root mean square error of prediction of 5.161. The study of Aboonajmi et al., (2016) investigated egg freshness using visible near infrared spectroscopy at a wavelength range of 300-1000 nm and the spectra were analyzed using radial basis function resulting in correlation coefficient of 0.745. The success of application of near-infrared spectroscopy for the development of classification models can be based on high accuracy.

Near-infrared spectroscopy (NIRS) is based on the absorption of electromagnetic radiation by the molecules of a sample at a specific wavelength from 700 nm to 2500 nm (Osborne et al., 1993). The study used this technique to evaluate the freshness of free-range chicken eggs and the spectra that were gathered were analyzed using machine learning algorithms including Support Vector Classification, Naïve Bayes Classifier and Stepwise discriminant analysis. Support vector classification is a supervised machine learning algorithm that finds a hyperplane separating different classes particularly in the current study the gaussian kernel was used which allows support vector classification to create a non-linear decision boundaries by mapping input features into a higher dimensional space (Muthukrishnan and Udaya Prakash, 2022). A classic advantage of SVC is that it can handle complex relationships between features and is robust to overfitting in well-tuned models. Naïve bayes is based on Bayes Theorem that predicts the class with the highest posterior probability given the input features. Different machine learning algorithm was used in the development of the classification model with the enhancement of Bayesian optimization. The algorithms were used to predict the hyperparameters of the succeeding iteration based on the results of the previous iteration (Yang and Shami, 2020). Stepwise discriminant analysis was also used in the current study because it is good in selecting the most relevant features for discriminating between two or more groups by adding or removing predictor variables step by step.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue X, October 2025

There has been no report on the investigation of free-range chicken eggs that are locally produced in the Philippines in terms of freshness using NIRs. The increasing production of free-range chicken not only in the province and other areas nationally will definitely strengthen its potential for the production of eggs and improve the management programs.

II. Methodology

Sample Collection and Preparation

A total of 595 egg samples from Dekalb brown and Dominant Cz were collected from three distinct poultry farms: (1) Tuyo Farmers Agricultural cooperative; (2) the BPSU DA-ACEF FRC Funded Project located at the BPSU Abucay Campus; and (3) HARBC Poultry Farm in Abucay, Bataan. The eggs obtained from Tuyo Farmers Agricultural cooperative came from hens with an average age of 44 weeks and an average egg weight of 56.387 g ± 0.0977 g. Similarly, hens from HARBC Poultry Farm were 44 weeks old, with their eggs averaging 56.959 g ± 0.105 g. At the BPSU DA-ACEF facility, the chickens were 46 weeks old, and the corresponding egg samples had an average weight of 56.390 g ± 0.244 g. The eggs were monitored over a 21-day storage period and scanned at seven time points: days 0, 4, 7, 10, 14, 17, and 21. From the total sample pool, 85 eggs were selected for detailed analysis of freshness over time. Spectral data were acquired using an average of eight scans per egg to minimize spectral noise and scattering. Optimizing the number of scans was essential to enhance signal clarity and ensure the reliability of the spectral measurements.

Preliminary Testing

Preliminary testing was conducted to ensure the accurate acquisition of egg spectral data while minimizing interference from noise and light scattering. This step also considered key freshness indicators, particularly the Haugh Unit, to provide a comprehensive baseline for analysis. Spectral data were obtained using a Diffuse Reflective Module (NIR-M-R2) spectrometer, with each egg positioned directly beneath the device to ensure consistent and reliable reflectance measurements.

Reference Analysis

The Haugh Unit (HU) is the standard method for assessing internal egg quality and is widely recognized as a reliable indicator of egg freshness (Yuan et al., 2023). After weighing, the eggs were carefully broken onto a glass break-out table to facilitate the measurement of albumen height. The height of the thick albumen was measured at three distinct points, approximately 10 mm away from both the yolk and the outer edge of the thick albumen, using a vernier caliper. The mean of these three values was then calculated and used in the Haugh Unit computation. The higher the number, the better the quality of the egg. The Haugh unit value ranges from 0 to 130 wherein AA (72 or more), A (71-60), B(59-31), C (30 or less). Eggs harvested in a poultry farm should have an average HU of 75 to 85. The Haugh Unit (HU), calculated using Equation 1, served as the reference method for assessing egg freshness. The computed HU was then categorized as AA, A, B, and C.

$$HU = 100 \times \log(h - 1.7w^{0.37} + 7.6)$$

Where:

HU = Haugh unit

h = height of the albumen (mm)

w= weight of the eggs (g)

Collection of Spectra using Portable NIR Spectrometer

A Diffuse Reflective Module (NIR-M-R2) was employed to collect the spectral data of both egg white and yolk samples, utilizing an Enhanced Vision Module (EVM) with a spectral resolution of 10 nm across the wavelength range of 900 nm to 1700 nm (Texas Instruments, 2023). Spectral scanning was performed continuously from day 0 to day 21 at two different orientations—vertical and horizontal—as illustrated in Figure 1 and 2, to determine the optimal measurement position.

For vertical positioning (Position 1), eggs were placed upright in an egg tray, with the spectrometer directed at the blunt end of each egg. This region contains a small air cell located between the inner and outer shell membranes, which may influence spectral reflectance. The estimated scan time per sample was approximately 3.817 seconds, during which the NIR-M-R2 device transmitted the spectral data to the computer, providing the corresponding wavelength readings. Subsequently, once the spectral data for eggs in the vertical position were obtained, the same procedure was applied for horizontal positioning (Position 2). Spectral data—including wavelength measurements—were likewise collected for comparative analysis between the two orientations.

Spectral Pretreatment

The acquired spectral data underwent a series of pretreatment procedures to minimize the effects of light scattering and spectral noise, which are commonly encountered in near-infrared (NIR) analysis. Light scattering, a physical phenomenon frequently observed in NIR spectroscopy, can introduce unwanted variation by causing the light to deviate from its intended path and follow alternate trajectories . These deviations can adversely affect the accuracy and robustness of predictive models.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue X, October 2025

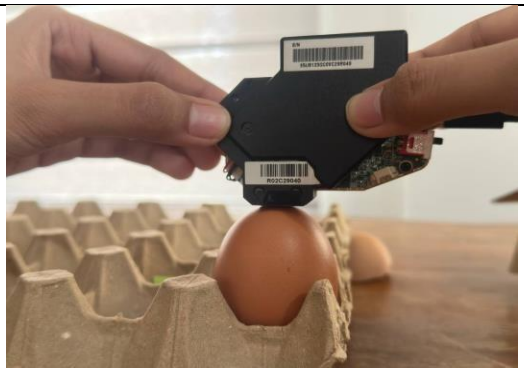

Fig. 1 Capturing of Spectral data using a portable NIR Spectrometer (vertical position)

Fig. 2 Capturing of Spectral data using a portable NIR Spectrometer (horizontal position)

To address this, a combination of pretreatment techniques was applied to reduce interference caused by offset, dispersion, and spectral overlap, while enhancing signal smoothness (Wahyudi et al., 2023). As reported by Kusumiyati et al. (2021), Standard Normal Variate (SNV) is a widely used method for correcting scatter-related distortions. Additionally, the Savitzky–Golay first derivative technique was employed to mitigate noise, and Moving Average Smoothing was applied to further filter residual fluctuations. Together, these methods contributed to improving the reliability and interpretability of the spectral data for subsequent modeling.

Outlier removal

The collected data were initially organized in a Microsoft Excel spreadsheet. Outliers—defined as samples that significantly deviated from the majority of the population in terms of Haugh Unit values and spectral characteristics—were identified and removed using the Z-score method. The Z-score is a statistical metric that quantifies how far a given value deviates from the mean of a dataset, expressed in terms of standard deviations (Nevil and Kindness, 2024). Typically, data points with Z-scores beyond the range of −3 to +3 were considered outliers and excluded from further analysis.Following the initial screening, the dataset was imported into The Unscrambler software for additional outlier detection. Principal Component Analysis (PCA) and the Hotelling's T^2 ellipse method were applied to assess data consistency and integrity. Samples that fell outside the 95% confidence ellipse in the PCA plot were classified as outliers and subsequently removed to prevent distortion of the analytical results (Samadi et al., 2022).Once outliers were eliminated, spectral data were preprocessed using a combination of techniques in The Unscrambler software. Standard Normal Variate (SNV) transformation was applied to correct for light scattering, while noise reduction was achieved through Savitzky–Golay smoothing and Moving Average Smoothing.

Development of classification model using Machine learning model

Several machine learning models were used in the study. Discriminant analysis is a statistical technique used to explore and evaluate differences between groups within a multivariate framework. To develop the classification model, Stepwise Discriminant Analysis (SDA) was employed. SDA is a variable selection method that iteratively identifies the most significant predictors while maximizing the model's discrimination power (Stąpor, 2015). Given the large number of spectral variables, initial models often demonstrated suboptimal performance. The use of SDA helped refine the model by focusing on the most relevant variables, thereby enhancing classification accuracy and reducing overfitting. SDA was performed using IBM SPSS Statistics 25. Naïve Bayes classifier and Support Vector classification was performed using the classification learner in MATLAB2025a using a 5 kfold cross validation. Then, for several machine learning used, Bayesian optimization was employed in the study. The response variable in the study is the classification of Haugh unit based on the reference value obtained during the conduct of the study. A classification learner was used in the classification of the Haugh Unit based on three classes (AA, B, C). In the support vector classification, the kernel function used was gaussian and since a Bayesian optimization was used, the following hyperparameter values was optimized

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue X, October 2025

including the box constraint level, kernel scale, multiclass coding and standardized data. For the Naïve Bayes classifier, the hyperparameters that was optimized include the distribution names and standardize data. A cross-validation accuracy for every training data set analyzed was obtained. The developed classification model was used in a test data set to validate the accuracy of the classification model developed. The basis for determining the best machine learning algorithm used in the analysis is the model that will obtain the highest cross validation accuracy and highest test set accuracy.

III. Results and Discussions

Spectral features of the free-range chicken egg samples

The near-infrared (NIR) spectra of free-range chicken egg samples were obtained within the wavelength range of 900 nm to 1700 nm. The NIR spectrum results from the absorption of NIR radiation by the sample, which induces molecular vibrations that manifest as distinct peaks and troughs across the spectrum. According to Samadi et al. (2022), such spectral patterns reflect the interaction between electromagnetic wave radiation and organic compounds, thereby enabling the identification of specific molecular constituents.

The spectral absorbance curves of chicken eggs collected from all farms were presented in Fig.3 for position 1 and Fig. 4 for position 2. In comparing scanning positions, Position 1 demonstrates a greater degree of light dispersion relative to Position 2. This effect is attributed to the increased curvature at Position 2, which likely enhances the interaction between incident light and the sample surface, thereby contributing to a broader spectral profile. As noted by Williams et al. (2019), this noise is attributable to electrical signals that reach the detector independently of the sample's actual spectral data, potentially interfering with accurate spectral interpretation. This broader curvature likely resulted from the increased surface variability in that orientation, which can alter light trajectory and cause deviations in detector readings.

Fig. 3 illustrates that the key absorption peaks contributing to spectral performance were located at 930.106 nm and 1446.05 nm. In contrast, Fig. 4 shows primary peaks at 930.106 nm and 1453.57 nm. The presence of a minor peak corresponding to the third overtone of C–H stretching may suggest the presence of carbohydrates in the egg, consistent with findings by Ghaderi et al. (2024). Moreover, the dominant absorption band observed around 1440 to 1485 nm, associated with the first overtone of O–H stretching, supports previous reports by Sahachairungrueng et al. (2023) indicating that water is a major component of egg composition.

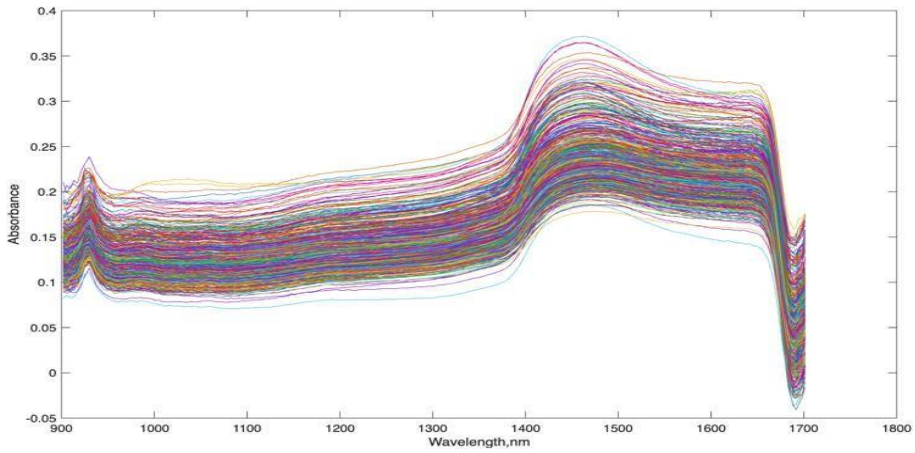

Fig. 3 Spectral data of the free-range chicken egg taken at position 1

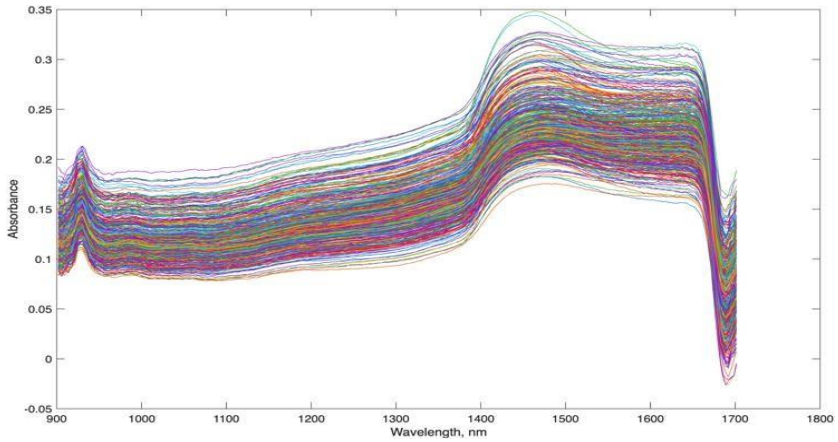

Fig.4 Spectral data of the free-range chicken egg taken at position 2

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue X, October 2025

Fig. 5 shows the mean spectral data of the free range chicken egg at position 1 categorized into three different classes: AA, A, and B. Based on Fig. 5, a higher absorbance was observed at AA class. The composition of the albumen, yolk, and cuticle changes during storage (Cruz-Tirado et al, 2021). During aging, the air cell height increases because moisture and gases escape through the shell, causing air to enter and expand the air space inside the egg.

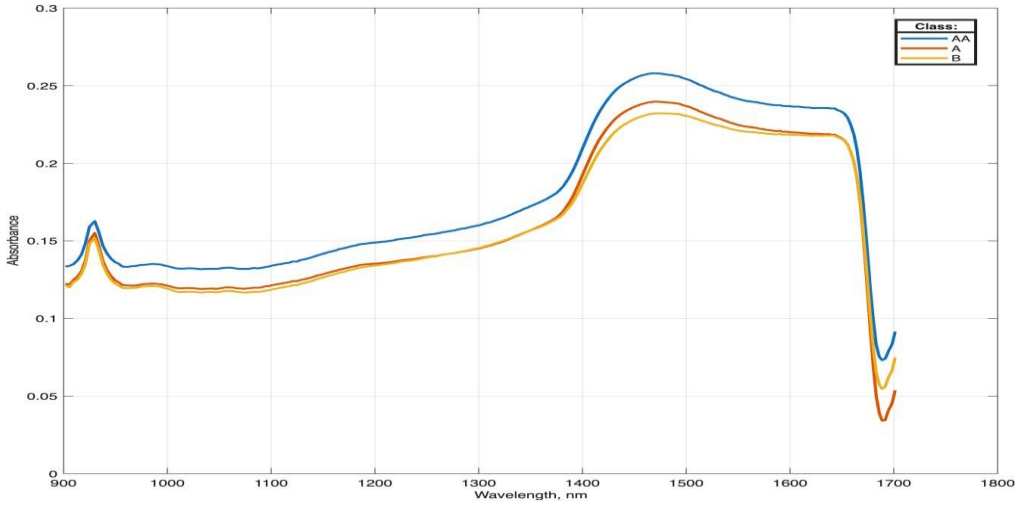

Fig. 5 Mean spectral data obtained from the egg samples with different Haugh unit.

Reference Analysis

The Haugh unit obtained for the different farms were shown in Table 1. The obtained Haugh unit can be classified as AA, A, and B.

Table 1. Haugh unit of the FRC egg obtained from three different poultry farm.

Farm	Minimum	Maximum
Tuyo Farmers Agricultural cooperative	47.10	74.14
BPSU	47.23	77.95
HARBC	44.50	82.16

Developed Classification Model

The best classification model developed for position 1 was observed at the data obtained from the BPSU DA-ACEF FRC Funded Project having a cross-validation training accuracy of 68.2 % and a test set accuracy of 63.6 % using SDA as shown in Table 2. For position 2, the best classification model was provided by the Naïve Bayes classifier for the data obtained from HARBC farm with a cross-validation accuracy of 70.70 % and a test set accuracy of 60.40 %. Table 2 and 3 shows the best classification model obtained from the combination of different pretreatment method analyzed using several machine learning algorithms. Among the different farms, a variable accuracy was obtained. This discrepancy suggests potential data heterogeneity between the training and test sets, highlighting variability in sample characteristics that may have affected the model's generalization performance.

Table 2. Classification accuracy of the model developed from position 1 using different machine learning algorithm.

Farm	Pretreatment	Machine Learning Algorithm	Accuracy	
			CV* accuracy	TS** accuracy
Tuyo Farmers Agricultural cooperative	Savitzky Golay 1st derivative (sp=3)	Naïve Bayes	60.10%	46.70%
BPSU	Savitzky Golay 1st derivative (sp=7)	SDA	68.20%	63.60%
HARBC	SNV and Sav- Gol 1D (sp=7)	SDA	75.5 %	58.3 %

*CV = cross-validation

**TS = test set

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue X, October 2025

Table 3. Classification accuracy of the model developed from position 2 using different machine learning algorithm.

Farm	Pretreatment	Machine Learning Algorithm	Accuracy	
			CV* accuracy	TS** accuracy
Tuyo Farmers Agricultural cooperative	Savitzky Golay 1st derivative (sp=3)	Naïve Bayes	62.80%	57.80%
BPSU	SNV+ Savitzky Golay 1st derivative (sp=3)	SVM	68.10%	55.60%
HARBC	Savitzky Golay 1st derivative (sp=3)	Naïve Bayes	70.70%	60.40%

*CV = cross-validation

**TS = test set

Sample Cluster based on Discriminant Functions

The scatter plot for Position 1 in Figure 6a reveals the formation of distinct clusters; however, some overlap remains among specific data points, indicating limited separation between certain classes. Despite this overlap, the classification of Class B samples in Position 1 appears to be more distinct and reliable. This observation aligns with the findings of Cruz-Tirado et al. (2021), who reported that the presence and expansion of the air cell during storage enhances classification accuracy. As eggs are stored for longer periods, the air cell enlarges, thereby facilitating the separation of quality grades based on internal characteristics. Moreover, the data demonstrate a clear trend wherein lower-grade samples (e.g., Class B) are more spatially distant from higher-grade samples (Class AA and A), supporting the model's capacity to separate eggs based on freshness and internal quality.

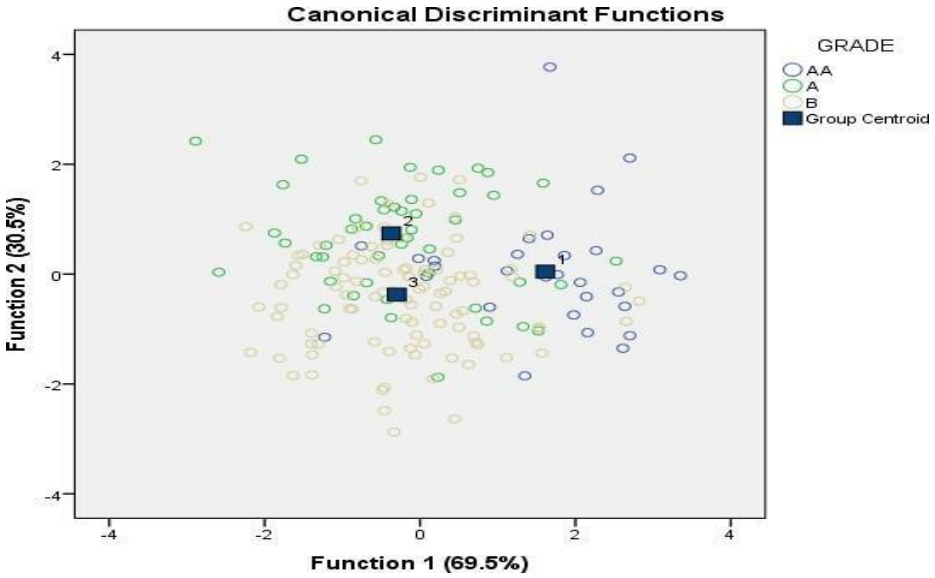

Figure 6. Scatter plot between first two canonical discriminant functions derived from canonical discriminant functions derived from BPSU DA-ACEF FRC Funded Project (a) position 1

Conclusions

Based on the study conducted, the following conclusions were drawn. The spectral data gathered from positions 1 and 2 indicated the presence of two prominent peaks, extending from 1440 to 1485 nm and 930 nm, during the egg's storage period. To develop a classification model, there were criteria to be followed. The acquired data must possess utmost precision in both its cross-validation and test set. The results indicated that BPSU DA-ACEF FRC Funded Project achieved the best level of accuracy throughout both cross-validation and test set, with percentages of 68.20% and 63.60% respectively. It is recommended to improve the classification model by using several dimensional reduction tools for increased model performance.

Acknowledgement

The authors extend their sincere appreciation to the BPSU Research and Development Office, for its unwavering support to the researchers.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue X, October 2025

References

1. Aboonajmi, M., Saberi, A. H., Najafabadi, T. A., Kondo, N. (2015). Quality Assessment of Poultry Egg Based on Visible–Near Infrared Spectroscopy and Radial Basis Function Networks. International Journal of Food Properties, 19(5), 1163–1172. https://doi.org/10.1080/10942912.2015.1075215
2. Akowuah, T, Teye, E., Hagan, J., Nyandey, K. 2020. Rapid and nondestructive determination of egg freshness category and marketed date of lay using spectral fingerprint. Journal of spectroscopy. https://doi.org/10.1155/2020/8838542
3. Cruz-Tirado, J. P., Lucimar da Silva Medeiros, M., 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
4. English, M. (2021). The chemical composition of free-range and conventionally farmed eggs available to Canadians in rural Nova Scotia. Canadians in rural Nova Scotia. PeerJ. doi: 10.7717/peerj.11357. PMID: 33987025; PMCID: PMC8103914.
5. Ghaderi, M., Mireei, S. A., Masoumi, A., Sedghi, M., Nazeri, M. (2024). Fertility detection of unincubated chicken eggs by hyperspectral transmission imaging in the Vis- SWNIR region. Scientific Reports, 14(1). doi.org/10.1038/s41598-024-51874-2
6. Grashorn, M. (2016). Effects of storage conditions on egg quality. Retrieved from: https://lohmann-breeders.com/media/2020/08/VOL49-GRASHORN-Storage.pdf
7. Kusumiyati, K., Mubarok, S., Sutari, W., Hadiwijaya, Y. (2021). Application of spectra pre- treatments on firmness assessment of intact sapodilla using vis-nir spectroscopy. IOP Conference Series, 644(1), 012001. https://doi:10.1088/1755-1315/644/1/012001
8. Muthukrishnan, R. and Udaya Prakash, N. (2022). Exploration of Kernel Functions in Support Vector Classification.International Journal of Statistics and Reliability Engineering. Vol. 9(2), pp. 318-321.
9. Nevil, S. and Kindness, D. (2024). Z-Score: Meaning and Formula. Investopedia. https://www.investopedia.com/terms/z/zscore.asp
10. Osborne, B.G., Fearn, T., Hidle, P.H. (1993). Practical NIR spectroscopy with applications in food and beverage analysis.
11. PNS/BAFS 262(2018). Philippine National Standard. Free range chicken.
12. Sahachairungrueng, W., Thompson, A. K., Terdwongworakul, A., Teerachaichayut, S. (2023). Non-Destructive classification of organic and conventional hens' eggs using Near-Infrared Hyperspectral Imaging. Foods, 12(13), 2519. https://doi.org/10.3390/foods12132519
13. Samadi, N., Wajizah, S., Zulfahrizal, Z., Munnawar, A. A. (2022). Near Infrared Technology for Determining Cacao Pod Husk Quality Attributes as Animal Feed by means of PLSR Approach. IOP Conference Series. Earth and Environmental Science, 995(1), 012010. doi.org/10.1088/1755-1315/995/1/012010
14. Stapor, K. (2015). Better Alternatives for Stepwise Discriminant Analysis. Acta Universitatis Lodziensis. Folia Oeconomica, 1(311). ttps://doi.org/10.18778/0208-6018.311.02
15. Texas Instruments. (2023). Texas Instruments. https://www.ti.com/tool/DLPNIRSCANEVM
16. Wahyudi, I., Munawar, A. A., Yu, P., Samadi, S. (2023). Optical characterization of NIR spectra for chemomectric model of cocoa pod husk fermented for animal feed. IOP Conference Series, 1183(1), 012003. https://doi.org/10.1088/1755-1315/1183/1/012003
17. Williams, P., Antoniszyn, J., Manley, M. (2019). Egg freshness detection based on digital image technology. Scientific Research and Essay Vol.4 (10), pp. 1073-1079. https://academicjournals.org/journal/SRE/article-full-text-pdf/850D77C18544
18. Xie, S., Hai, C., He, S., Lu, H., Xu, L., Fu, H. (2023). Discrimination of Free-Range and caged eggs by Chemometrics analysis of the elemental profiles of eggshell. Journal of Analytical Methods in Chemistry, 2023, 1–8. doi.org/10.1155/2023/1271409
19. Yang, L., and Shami, A. (2020). On hyperparameter optimization of machine learningalgorithms: Theory and practice, Neurocomputing. 415 295–316, https:// doi.org/10.1016/j.neucom.2020.07.061
20. Yuan, L., Fu, X., Yang, X., Chen, X., Huang, G., Chen, X., Shi, W., Li, L. (2023). Non- Destructive Measurement of Egg's Haugh Unit by Vis-NIR with iPLS-Lasso Selection. Foods, 12(1), 184. doi.org/10.3390/foods12010184