Non-destructive detection of lamb freshness based on flexible impedance sensor

SHIQIAN WANG – XIAOSHUAN ZHANG – MARTIN POLOVKA – BLANKA TOBOLKOVÁ

Summary

A non-destructive method to monitor lamb freshness was developed by analysing the impedance spectrum of lamb meat. As a result of lamb storing, its biological tissue structure and intracellular ionic conductivity change, which can be effectively monitored by impedance amplitude and phase angle. Initially, the coefficient of variation method was employed to identify three frequency ranges: low, medium, and high. These ranges were used to establish a predictive model for lamb freshness using Fisher linear discriminant analysis. Independent variables included impedance, phase angle, and measurement quality, while dependent variables encompassed fresh and aged lamb meat states. The subsequent evaluation of lamb meat morphology aimed to uncover how these independent variables impacted lamb freshness. Results highlighted the significance of impedance parameters in fresh lamb meat, particularly in the low-frequency range. The discriminant analysis model demonstrated a robust predictive capacity, achieving a 94% accuracy rate for the discriminant function. The impedance variable had a significant impact on the model accuracy, and the introduction of independent variables improved the predictive accuracy of fresh and aged lamb meat by 22% and 15% respectively. Moreover, the study observed interconnected relationships among lamb freshness, water status, and impedance state changes.

Keywords

lamb; freshness; impedance; flexible sensor; prediction model

Lamb has long held a significant place in global culinary traditions [1]. The freshness of lamb plays a crucial role in determining its quality. High freshness ensures a tender taste, rich nutrition and retention of more high-quality proteins [2]. However, prolonged or improper storage reduces the freshness of lamb [3], impacting its quality when placed on the market. This, in turn, affects the economic interests of stakeholders [4]. Hence, there arises a need for a rapid and efficient method to assess lamb freshness.

Indicators of lamb meat freshness can be divided into three main categories: physical, physiological and biochemical. Physical indicators comprise colour, water content and density [5]. Recent research on these involved various technologies like X-ray, thermal imaging, infrared spectroscopy or hyperspectral imaging as effective means to characterize lamb meat freshness [6–8]. Physiological indicators encompass factors such as elasticity, odour and cellular water content [9]. Biochemical indicators include protein content and enzyme activity. Current techniques used to evaluate physiological and biochemical indicators of lamb freshness require destruction of samples, rendering them unsuitable for assessing freshness during the sorting processes [10]. In contrast, non-destructive methods based on physical properties monitoring offer promise at a good detection level. However, while parameters like colour, moisture content, density and spectral information can indicate lamb freshness to some extent [11], they do not provide comprehensive understanding of freshness loss stemming from changes in microstructure, such as internal cellular and moisture status during aging and deterioration. Conse-

Shiqian Wang, Xiaoshuan Zhang, Beijing Laboratory of Food Quality and Safety, College of Engineering, China Agricultural University, No. 17 Qinghua East Road, 100083 Beijing, China.
Martin Polovka, Blanka Tobolková, Department of Chemistry and Food Analysis, Food Research Institute, National Agricultural and Food Centre, Priemyselná 4, 82475 Bratislava, Slovakia.

Correspondence author
Xiaoshuan Zhang, e-mail: zhxshuan@cau.edu.cn

quently, an urgent need exists for a non-destructive sorting method that can identify lamb meat of high freshness, ultimately benefiting consumers looking for the top-quality products.

Zhao et al. [12] applied the basic theory of electrical impedance spectroscopy (EIS) to biological tissues and two commonly used measurement methods, summarized the application of EIS technology in fish quality evaluation and concluded that EIS has the advantages of being fast, non-destructive, inexpensive, easy to implement and saving costs and time. It represents a stable linear system, if a sinusoidal current $I(t)$ of angular frequency (ω) is fed into the system as a disturbance signal, the output response $V(t)$ of the system is also a sinusoidal voltage of ω.

EIS can be used to identify the quality characteristics of meat. By measuring the electrical impedance response of meat at different frequencies, information related to meat quality, such as moisture content, protein content or cell structure can be obtained. This information can be used to determine the freshness of the meat, the storage conditions and the treatment method. Electrical impedance spectroscopy can even be used to evaluate the freezing and thawing process of meat. Freezing and thawing affect the cellular structure and tissue properties of meat, which in turn change its electrical impedance response. By monitoring changes in electrical impedance over time and frequency, the effect of temperature changes on meat quality can be assessed. There should be a correlation between the electrical impedance response obtained from EIS measurements and the freshness index of meat. The correlation between the electrical impedance characteristics and freshness needs to be determined through experimental studies and data analysis. This may involve physical characteristics related to freshness such as moisture content, protein degradation or bacterial contamination. It is important to ensure that the selected electrical impedance characteristics can accurately and sensitively reflect the changes in freshness of meat. To build a reliable predictive model, a calibration and validation process is required. The calibration phase uses a series of samples of known freshness status to make measurements, collect electrical impedance data and correlate them with the corresponding freshness metrics. The performance and accuracy of the model is then evaluated using an independent set of validation samples. The design and execution of the calibration and validation process is critical to the applicability of the results.

This novel technique, EIS, has been used in various instances to non-destructively analyse the moisture and cellular conditions of biological tissues [13]. However, when applied to stored lamb, the impedance spectral fitting error was deemed unacceptable due to the tissue‘s anisotropic microstructure and the presence of necrotic tissue. Consequently, this study employed impedance selection points to assess lamb meat freshness. The primary goal was to develop an evaluation model using the EIS selection frequency method for non-destructively determining the freshness of lamb meat.

MATERIALS AND METHODS

Lamb ingredients

Two types of meat were chosen for this study. The first, from Maoshan sheep, which hails from mainland China and is primarily bred in regions like Guangxi, Sichuan and Yunnan. The specimens used were processed by Yunnan Honghe Meideng, which is based in Honghe Prefecture, Yunnan Province, China. The second meat type was from Jianghan sheep, which is a prevalent sheep breed originating from areas such as Hubei, Hunan or Henan in mainland China. Known for its tender meat with minimal fascial tissue, it is a crucial breed in the region [14]. For freshness testing, both fresh lamb and naturally aged lamb were selected. It is important to note that these were of the same breed sourced from identical lamb lots. Lamb meat, mostly taken from leg muscle tissue with minimal fascial tissue and no breakage, typically holds a moisture content of 65–70 %. For this study, two pieces of fresh lamb, both with approximately 70% moisture content, were employed – labelled as Experimental lamb I and Experimental lamb II. Experimental lamb I, initially stored at 4 °C and stabilized at approximately 25 °C in room temperature conditions, underwent impedance and phase angle peak measurements at temperature intervals of 4 °C, 11 °C, 18 °C and 25 °C (Fig. 1). Meanwhile, Experimental lamb II, subjected to moisture reduction via a dryer at room temperature, represented the simulated aging process. As lamb ages, it undergoes internal changes involving cellular rupture, protein disintegration, fat oxidation and water loss, leading to a noticeable decrease in freshness compared to freshly obtained lamb [15]. Balasubramanian et al. used a customized metal oxide-based olfactory sensing system to analyse beef tenderloin and used the extracted features to develop a classification model using a radial-basis function neural network, which did have a positive impact on improving the classification

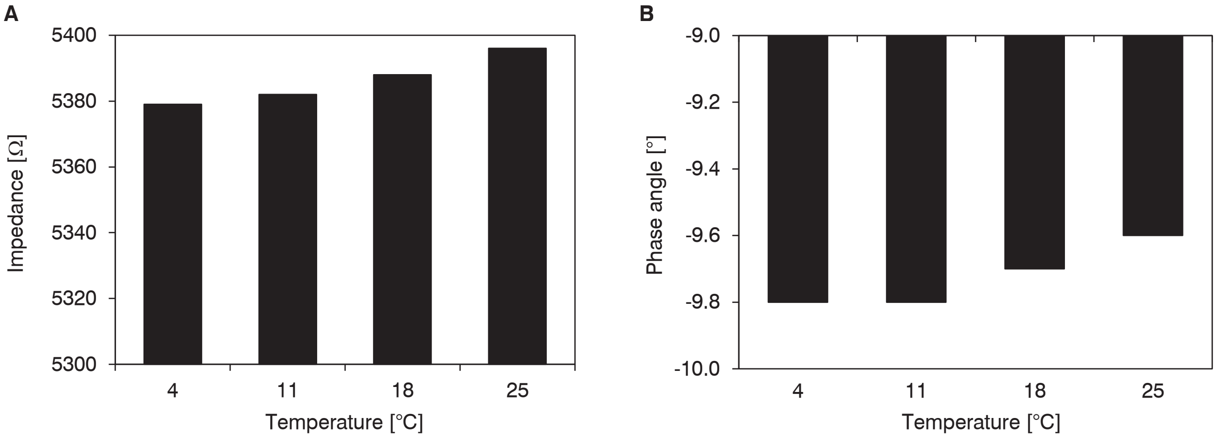

Fig. 1. Histograms of impedance and phase angle peaks as a function of temperature.

A – impedance. B – phase angle.

accuracy obtained [16]. To construct a prediction model, 50 samples of lamb were allocated as the training set and another 50 as the test set, ensuring an equal split between the fresh and aged lamb in both sets.

Experimental principle

The lamb's skeletal muscle, derived from selected materials, comprises bundles of myofibers, each composed of numerous individual myofibers. These myofibers consist of myogenic encased in sarcoplasm. Sequentially, these myogenic fibres form a series of muscle segments separated by z-discs. In this model, it is assumed that the myoplasm, primarily composed of water and proteins, exhibits resistive electrical behaviour. Additionally, parallel myosegments are also assumed to be resistive. The alternating arrangement of myosegments and z-discs contributes to the capacitive behaviour observed within the skeletal muscle fibres [17]. However, these simplifications regarding resistive and capacitive behaviour are only applicable when concerning the muscle fibres direction due to geometric aniso-

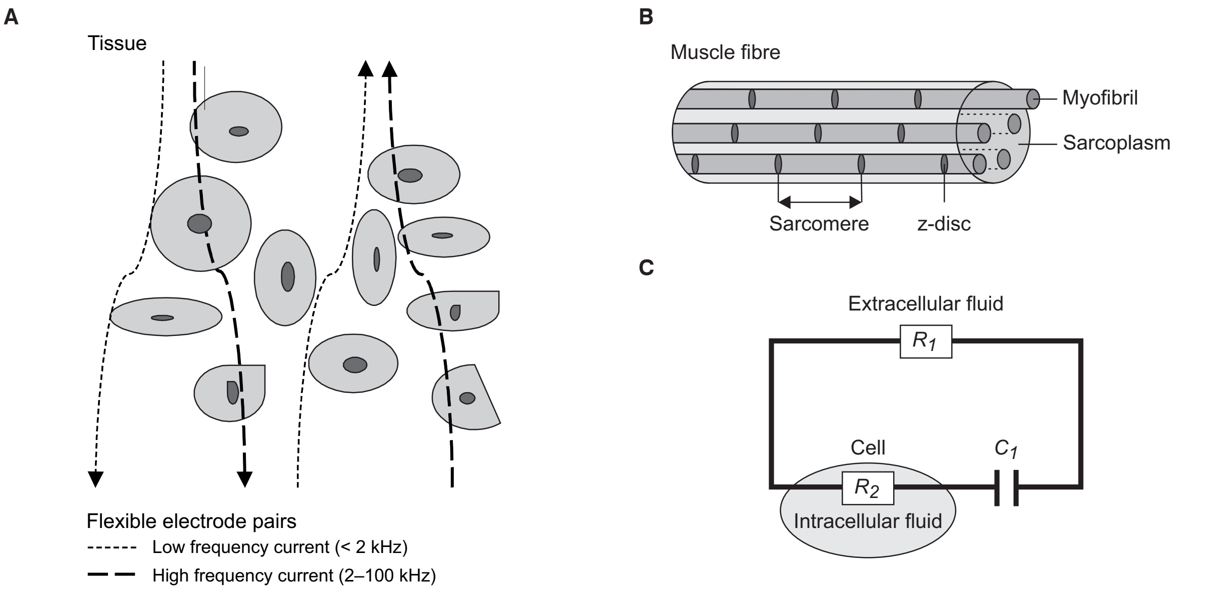

Fig. 2. Experimental principle and equivalent circuit diagram.

A – schematic diagram of low and high frequency currents flowing through tissue cells, B – simplified geometric model of skeletal muscle fibres, C – model equivalent circuit diagram.
R_1 – resistive behaviour of the muscle mass, R_2 – resistance of sarcomer, C_1 – capacitance resistance of z-disc.

tropy [18]. The equivalent circuit diagram of this model is depicted in Fig. 2.

It is assumed that R_1 represents the resistive behaviour of the myotome. R_2 and C_1 in series represent alternate myotome segments and z-discs. The bioimpedance (Z) of the model muscle can be determined as

$$Z = \frac{R_1 + j\omega R_1 R_2 C_1}{1 + j\omega C_1 (R_1 + R_2)} \quad (1)$$

where j is the imaginary unit and ω denotes the frequency. Therefore, the impedance magnitude is shown in Eq. 2.

$$|Z| = \frac{\sqrt{[R_1 + \omega^2 R_1 R_2 C_1^2 (R_1 + R_2)]^2 + (\omega R_1^2 C_1)^2}}{1 + \omega^2 C_1^2 (R_1 + R_2)^2} \quad (2)$$

Muscle contraction leads to shortening of the myosegmentum, which decreases the distance between z-discs. This increases the capacitance, which corresponds to a decrease in reactance. As in the passive first-order circuit shown in Fig. 2, the impedance amplitude decreases over the entire frequency range.

$$\Phi(Z) = -\arctan\left(\frac{\omega C_1 R_1^2}{R_1 + \omega^2 C_1^2 R_1 R_2 (R_1 + R_2)}\right) \quad (3)$$

where $\Phi(Z)$ is the phase angle of the impedance Z.

According to previously given assumptions, muscle contraction is associated with an increase in C_1, which leads to a compression of the phase response in the frequency dimension. In the logarithmic frequency representation, this corresponds to a shift of the phase response to lower frequencies. This particular behaviour is the theoretical basis for the phase effect. The values of R_1 and R_2 are also affected by muscle contraction but, based on previous measurements, it is assumed that these relative changes are less than those of C_1.

Impedance measurement

The impedance analyser IM3570 (Hioki, Nagano, Japan) was used for data measurement, along with the measurement system and material samples [19]. In this experiment, the measurement accuracy level of our IM3570 sensor was level 0.1 and the error range was ± 0.5 %. Under this accuracy, suitability of the model may be guaranteed. To prepare the electrodes for impedance measurements, the clamping fixture adjusts the force while the graphene pattern is printed onto the polyimide film by a laser cutter based on a photothermal reaction. This could be confirmed by previous studies [20, 21]. Specifically, a self-designed fork finger-type impedance electrode was employed in-house to enhance signal precision and accuracy, as well as to minimize external interference [22]. The laser scanning parameters were as follows: single scan with 120 mm·s^{-1} speed, 7.2 W power, 0.02 mm line spacing and 8 mm Z-axis spacing.

Before the measurement, short and open circuit corrections were conducted. Additionally, a thick slide was added behind the electrode sheet to exert pressure on the lamb sample, preventing its detachment from the bench during the measurements. The analysed samples were hind leg meat, uniformly shaped into 50 mm × 50 mm sample blocks to standardize subsequent electrode measurements. Each lamb piece reached the weight of approximately 4.5 g (with a controlled error within 5 %). The electrode was placed into the central part of the lamb, ensuring uniformity and minimizing the presence of other tissues and fascia [23].

The electrical parameters assessed were impedance (Z) and phase angle (θ) within a frequency range of 1–80 kHz, comprising 60 sampling points, considering the measurement frequency's polarization sensitivity when below 1 kHz. At each frequency point within this range, distinct impedance and phase angle values were obtained, both differing in magnitude across frequencies. These values collectively formed the EIS dataset.

Data analysis model

Statistical software SPSS version 27.0 (IBM, Armonk, New York, USA) was used to build the predictive model to predict the freshness of lamb, involving Fisher's linear discriminant analysis (FLDA) [24]. In contrast to some linear and non-linear regression models, such as partial least squares regression and least squares support vector machines that are used to build the predictive models, FLDA focuses on maximizing the variability between the different categories and therefore is better able to distinguish between meat samples of different freshness status.

The principle of FLDA application for binary classification problems is the projection of d-dimensional features into a one-dimensional space using a d-dimensional vector Φ. For the resulting low-dimensional projection, the different classes are as separate as possible, while the same class is as close as possible. X_1 and X_2 represent two training sets from two different classes.

$$X_1 = (x_{11}, \cdots, x_{1l_1}) \quad (4)$$

$$X_2 = (x_{21}, \cdots, x_{2l_2}) \quad (5)$$

where x_1 represents projection of samples, number 1 represents the ordinal number of the training set to which the sample belongs, l_1 represents the ordinal number of the sample in dataset X_1, x_2 represents projection of samples, number 2 represents the ordinal number of the training set to which the sample belongs, l_2 represents the ordinal number of the sample in dataset X_2.

The vector Φ is obtained by solving the following optimization problem:

$$\max J(\Phi) = \frac{|m_1 - m_2|^2}{S_1^2 + S_2^2} \tag{6}$$

where m_1 and m_2 are the projections of means X_1 and X_2, respectively. S_1^2 is the scatter variance of the projected samples of class X_1 and S_2^2 is the scatter variance of the projected samples of class X_2.

$$m_1 = \frac{1}{l_1}\sum_{j=1}^{l_1} \Phi^T x_{1j} \tag{7}$$

$$m_2 = \frac{1}{l_2}\sum_{j=1}^{l_2} \Phi^T x_{2j} \tag{8}$$

$$S_1^2 = \sum_{j=1}^{l_1} \left(y_{1j} - \mathrm{m}_1\right)^2 \tag{9}$$

$$S_2^2 = \sum_{j=1}^{l_2} \left(y_{2j} - \mathrm{m}_2\right)^2 \tag{10}$$

$$y = \Phi^T x \tag{11}$$

where T is mathematical notation for vector transpose, y is a variable that projects d-dimensional features into a one-dimensional space using a d-dimensional vector Φ.

The objective of maximizing vector $J(\Phi)$ is to find a vector that minimizes the within-class scattering while maximizing the mean of the projections between the classes. Undetermined coefficients in the discriminant function were determined using a large amount of data from the training set and calculating the discriminant index for the test set.

FLDA is a classical binary classification method for projecting samples onto a linear discriminant axis such that the distance between the similar samples is minimized and the distance between the dissimilar samples is maximized. In FLDA, there exists a vector optimization method to solve for the best discriminant axis. This vector optimization method is often referred to as the generalized eigenvalue problem. It involves computing the eigenvalues and eigenvectors of two matrices, the intra-class scatter matrix and the inter-class scatter matrix. The intra-class scatter matrix measures the degree of dispersion between samples of the same class, while the inter-class scatter matrix measures the degree of difference between the samples of different classes. By solving the generalized eigenvalue problem, the optimal discriminant axes (eigenvectors) can be obtained, allowing the projected samples to achieve the best classification results. At the same time, an important assumption of FLDA is that the eigenvalues of the sample in each category have the same covariance matrix.

ANOVA can be used to test whether this assumption holds true. By comparing the variance within and between the categories, it is possible to determine, whether the predictive model accurately captures the differences between the categories, and thus to calculate the adequacy of the model. The coefficient of variation (Cv) was introduced to compare the dispersion of the overall data for the measured parameters [25], defined as the ratio of the standard deviation to the mean:

$$Cv = \frac{\sigma}{\mu} \tag{12}$$

where σ is standard deviation and μ is mean.

This method was used to determine Cv impedance and phase angle (θ) at 50 frequencies in the training set.

In the data obtained above, the amplitude and phase angle of low, medium and high frequencies and the quality of the sample meat were taken, totalling seven variables. With the proposed model, the fitting relationship that exists between the freshness of mutton and each variable can be found out, and then a prediction model to predict the freshness can be built. Since these seven variables have different effects on the freshness of lamb, one can guess that the more variables involved in the prediction model, the more accurate, with less error and more stable the obtained prediction results.

RESULTS AND DISCUSSION

Environmental immunity test

To monitor and analyse the lamb freshness using electrode-measured parameters, a ten-day standardized experiment tracked the lamb's aging process. Due to its specific nature, the lamb was refrigerated. When transitioning the lamb from refrigeration to the experiment, gradual changes in surface temperature and humidity occurred due to room temperature conditions, influencing the impedance measurement. To address this phenomenon, the effect of temperature and humidity on the electrodes needed study. Moisture content decreased in 10% intervals from an initial 70 % humidity, resulting in moisture contents of 70 %, 60 %, 50 % and 40 %. Impedance and phase angle peak values for Experimental lamb II across these moisture contents were captured (displayed in

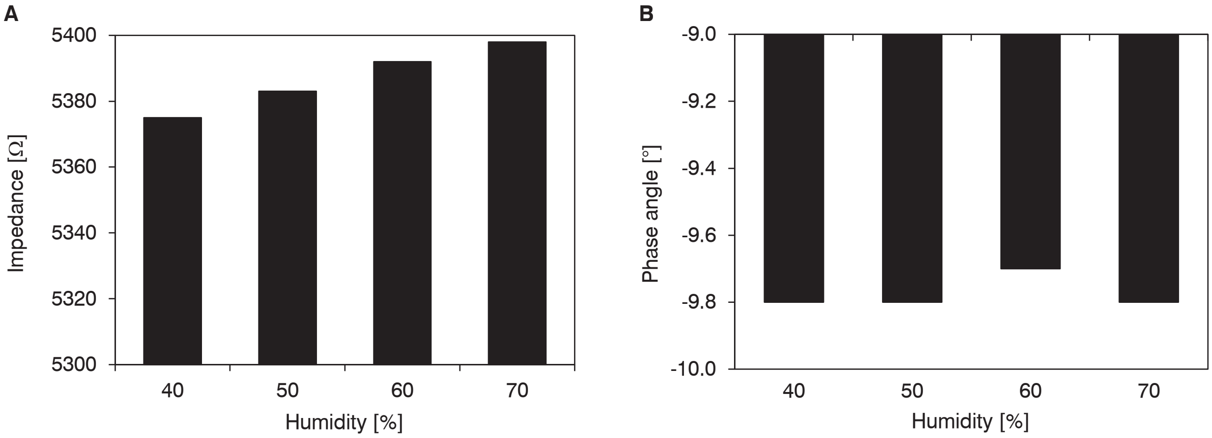

Fig. 3. Histograms of impedance and phase angle peaks as a function of humidity.

A – impedance, B – phase angle.

Fig. 3). As follows from the comparison of impedance and frequency changes due to temperature and humidity variations, a deviation of less than 0.2% in before-and-after measurements was evident. It is reasonable to assume, within the margin of error, that temperature and humidity alterations minimally affected the measured electrode parameters.

Impedance properties of lamb

Impedance (Z) and phase angle (θ) stand as pivotal parameters in EIS. To understand their relationship with lamb freshness, impedance and phase angle values were determined for individual lamb samples (measuring 50 mm × 50 mm sample blocks). In Fig. 4A and Fig. 4B, impedance values corresponding to various frequency responses are displayed. Across the different lamb breeds, within the same frequency response range, impedance values decreased with rising frequency. It is obvious, that the aged lamb exhibited higher impedance compared to fresh lamb. Fig. 4C and Fig. 4D illustrate the phase angle trend with frequency; as the frequency increased, the absolute value of the phase angle decreased.

Analysing the measured frequencies, they were segmented into low, medium and high frequency bands – below 1 kHz, 1 kHz to 10 kHz and above 10 kHz, respectively. Particularly in the low-frequency domain, the absolute values of impedance and phase angle were evidently larger for differently aged lamb compared to the high-frequency domain. This discrepancy in the impedance value and absolute phase angle size, typically observed in the low-frequency domain, serves as a distinguishing index for lamb freshness.

Further analysis involved examination of the coefficient of variation for impedance and phase angle, aiding in determination of the suitable independent variables applicable for the prediction model [9]. As is obvious from Fig. 5A and Fig. 5B, impedance *Cv* for aged lamb was lower than for fresh lamb and diminished with increasing frequency. As an illustration, at 1 kHz, *Cv* registered at 0.633 and 0.234 for Maoshan lamb and Jianghan fresh lamb, respectively. As frequency climbed to 60 kHz, *Cv* dropped to a minimum of 0.563 and 0.208, respectively. The phase angle's *Cv* followed a similar pattern, as shown in Fig. 5C and Fig. 5D. Considering the stability prediction, the high-frequency domain appears as a potential frequency range for impedance changes. However, this finding seems contradictory to the analysis of impedance variation across frequencies.

Fisher's linear discriminant analysis

Upon analysing the single electrode parameters in both the low and high frequency ranges, it is evident that individually they do not serve satisfactorily as fitting independent variables to meet the criteria for their applicability to discrimination. While the low-frequency domain shows potential in distinguishing lamb freshness, the model's prediction accuracy remains comparatively low due to high coefficient of variation. On the other hand, although the differences in impedance and phase angle values in the high-frequency region are not pronounced, the model exhibits a lower coefficient of variation, suggesting potentially enhanced prediction accuracy.

Low-frequency current predominantly traverses the extracellular fluid, while high-frequency current primarily navigates the intracellular fluid. This disparity in impedance parameters across

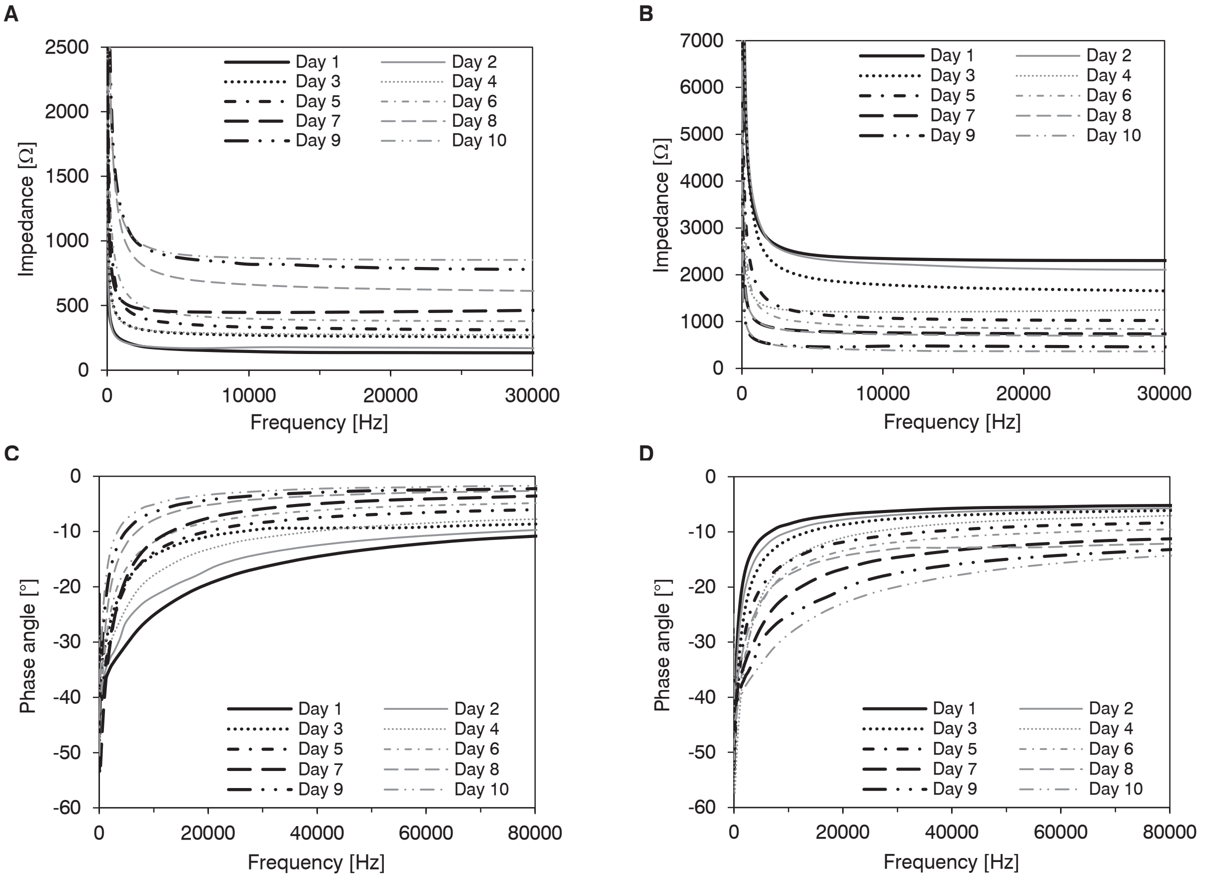

Fig. 4. Electrical impedance spectrum of lamb with different aging degree.

A – aged lamb, trend of impedance magnitude with frequency, B – fresh lamb, trend of impedance amplitude with frequency, C – aged lamb, trend of phase angle value with frequency, D – fresh lamb, trend of phase angle with frequency.

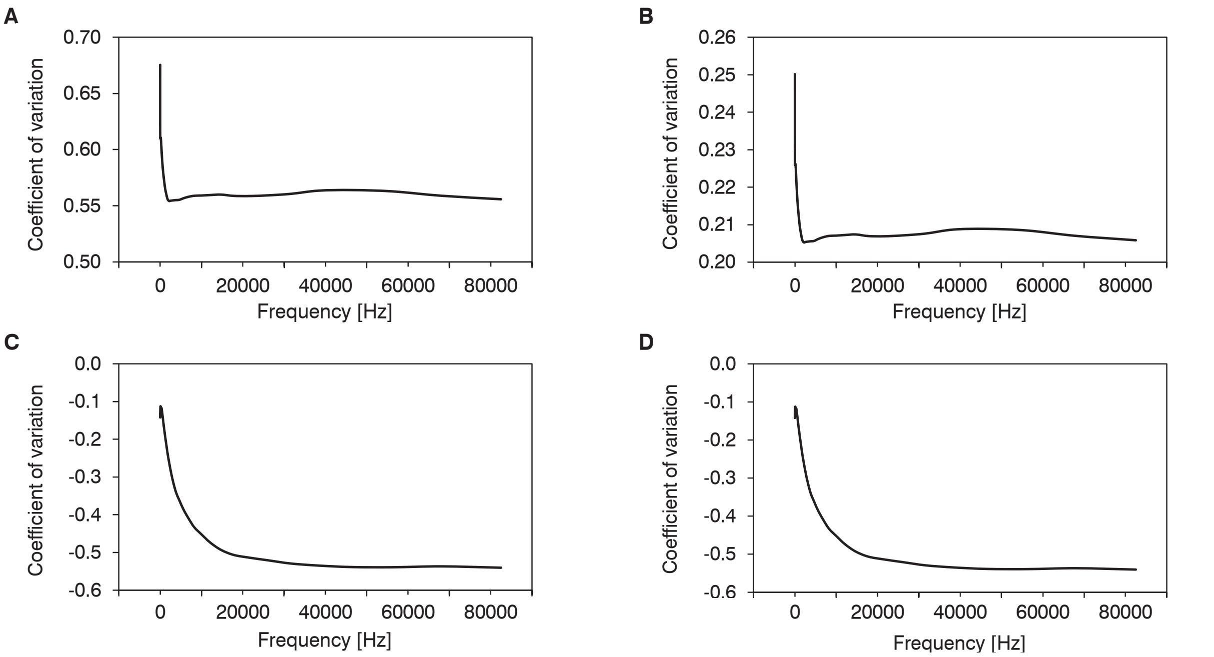

Fig. 5. Coefficient of variation for measurement parameters.

A – impedance variable coefficient values of aged lamb, B – impedance variable coefficient values of fresh lamb, C – phase angle variable coefficient values for aged lamb, D – phase angle variable coefficient values for fresh lamb.

the frequencies indicates the diverse lamb tissue information. To establish a more precise freshness discrimination model, specific frequencies across the different domains were selected. One frequency from each domain, chosen on the basis of coefficient of variation values, was employed as the model's selected frequency. This multi-electrode parameter model incorporates electrode parameters at various frequencies [26], providing deeper insights into lamb tissue changes.

Utilizing the impedance and phase angle values from the selected frequencies as independent variables, the model underwent discriminant analysis during the training (Tab. 1). As the mass of lamb may affect the electrode parameter values during freshness alterations of a single 50 mm × 50 mm piece, the mass at the time of measurement was included as an independent variable, maintaining control over the sample's initial mass consistency. For Maoshan lamb, the selected frequencies for independent variables were 1 kHz, 10 kHz and 60 kHz. FLDA model was employed for discriminant analysis. Independent variables X_1 through X_7 were defined, representing low, medium and high frequency impedance values (X_1, X_2, X_3) and phase angles (X_4, X_5, X_6), alongside the lamb's current mass (X_7). The model underwent the training and subsequent validation using distinct sets of training and validation data.

For the discriminant analysis, impedance values, phase angles and sample mass were selected, in a sequence followed from the discriminant model's analytical justification. The outcome demonstrated lower accuracy with fewer variables and higher accuracy with more variables. This confirmed that a sole electrical parameter or indicator is not a reliable measure of lamb freshness. There was a correlation evident among the various selected indicators. The initial analyses aligned with the set criteria, particularly when considering the accuracy needed to meet the discrimination requirements.

Model discussion

The here presented experiments were conducted to assess the impact of impedance values, phase angles, water content and micromorphology on lamb meat during natural aging. The obtained findings suggested that the developed prediction model, combining impedance values, phase angles and changes in lamb meat quality at specific frequencies, effectively detected and forecasted lamb meat freshness. This model considered sufficiently alterations in cell water content within the lamb, elements that could significantly influence sample quality during lamb meat aging, affecting impedance values and phase angles. Present study introduced a novel method for predicting lamb meat freshness and offers theoretical insights into characterizing lamb meat tissue and cellular structures using selected frequencies. There was a correlation established between the impedance spectra and lamb meat freshness.

Although Zhang et al. [4] applied an equivalent circuit modelling approach to measure the quality of meat including lamb, its accuracy was lower compared to results presented herein, particularly when dealing with lamb with low water content (≤ 45 %). In contrast, exact frequency selection similar to Bera et al. [27] in equivalent circuits, simplifies the characterization and is somewhat similar in capability. Aging lamb experiences shifts in water state, where the impedance value correlates with the proportion of combined water. The decline in antioxidant enzymes content during the lamb aging leads to cell membranes disruption and a subsequent decrease in bound tissue

Tab. 1. Lamb freshness prediction results based on linear discriminant analysis model and various input parameters.

No.	Independent variable	Discriminant function	Accurary [%]
1	Impedance, phase angle, mass	$0.002X_1 + 0.001X_2 + 0.001X_3 + 0.074X_4 + 0.129X_5 + 0.420X_6 + 0.742X_7 + 1.142$	94
2	Impedance, phase angle	$0.002X_1 + 0.001X_2 + 0.002X_3 + 0.100X_4 + 0.120X_5 + 0.408X_6 + 5.146$	87
3	Impedance, mass	$0.003X_1 - 0.001X_2 + 0.007X_3 + 0.204X_7 - 5.225$	82
4	Phase angle, mass	$0.263X_7 + 0.118X_5 + 0.441X_6 + 1.278X_7 + 18.799$	78
5	Phase angle	$0.259X_4 + 0.140X_5 + 0.477X_6 + 14.205$	75
6	Impedance	$0.002X_1 - 0.001X_2 + 0.007X_3 - 4.332$	72

X_1–X_7 were set as the independent variables. X_1 – low frequency impedance value, X_2 – medium frequency impedance value, X_3 – high frequency impedance value, X_4 – low frequency phase angle, X_5 – medium frequency phase angle, X_6 – high frequency phase angle, X_7 – current mass of the sample lamb.

Tab. 2. Comparison of flexible impedance sensor based lamb quality detection methods with other method models.

Object	Method	Input	Model	Accuracy	Feedback	Cost	Reference
Lamb	Gas sensor	O_2, CO_2, NH_3	SVM	93.9 %	Automatic	High	[31]
Duck meat	Fluorimetry	TVB-N	PLS	$R^2 = 0.881$	Manual	Lower	[32]
Fish	Colorimetric	pH	BPNN	92.6 %	Automatic	Low	[33]
Pork	UV-LED	Fluorescence image	PLSR	90.0 %	Automatic	High	[34]
Lamb	Flexible impedance sensor	Amplitude, phase angle	LDA	94.0 %	Automatic	Low	This work

UV-LED – ultraviolet light-emitting diode, TVB-N – total volatile base nitrogen, , R^2 – coefficient of determination.
Model: SVM – support vector machine, PLS – partial least squares, BPNN – back propagation neural network, PLSR – partial least squares regression, LDA – linear discriminant analysis.

water content, exacerbating tissue damage and microcrack formation in fresh lamb cells, which become denser and larger over time [28]. These changes contribute to higher impedance values in aged lamb. The interactions between micromorphology, water state and impedance are notable during the lamb aging [29]. Impedance comprises resistance and reactance, where resistance reflects water sensitivity and reactance mirrors morphology sensitivity. The interaction between the water morphology and microcracks impacts both impedance and phase angle [30]. Consequently, the freshness prediction model based on electrical parameter measurements at specific frequencies effectively predicts lamb freshness in its natural state. Moreover, the relationship between the water micromorphology and impedance supports the theoretical basis for lamb freshness evaluation.

Finally, comparison of the characteristics of the here presented method with other, previously developed methods of meat quality testing, is shown in Tab. 2. As is obvious, the flexible impedance sensor-based method developed for lamb quality detection reveals some portability compared to instrumental detection methods. Its simplicity is also comparable to other detection methods such as colorimetric labelling. In addition, the proposed method is less costly and can provide a reference for quality inspection in the meat supply chain.

CONCLUSIONS

Using flexible impedance electrodes and an electrochemical workstation, the impedance values and phase angles of fresh and aged lamb were measured in the high, medium and low frequency ranges. At the same time, the quality of the lamb meat was assessed, leading to the development of a lamb freshness identification model that has a strong predictive capability. The appropriate number of carefully selected variables, subsequently involved in the prediction model, can reduce the variability of prediction results and improve the accuracy and stability of the discrimination model. Presented results could represent progressive breakthrough in the quality testing of lamb meat, with potential to provide the missing tool for future freshness quality testing methods of lamb or other meats or other food products. The main conclusions can be summarized as follows:

1. The model's accuracy in predicting lamb freshness correlated positively with the number of independent variables incorporated, with the impedance value standing out as the primary parameter influencing prediction accuracy.
2. As a result of lamb ageing, notable changes occured within its cell structure, such as alterations in cell water content and protein composition, detectable via selected impedance characteristics.
3. Changes observed in the impedance of aged lamb meat reflected a combined impact stemming from alterations in water state and micro-morphology.
4. Presented results bear significance for lamb freshness categorization and offer potential applicability in testing the freshness of various other meats.

Acknowledgements

This study was supported by the earmarked fund for CARS-38 and Chinese-Slovakia bilateral cooperation programme supported by the Slovak Research and Development Agency (contract No. 2021-0023).

REFERENCES

1. Jayathilakan, K. – Sultana, K. – Radhakrishna, K. – Bawa, A. S.: Utilization of byproducts and waste materials from meat, poultry and fish processing industries: a review. Journal of Food Science and

Technology, *49*, 2012, pp. 278–293. DOI: 10.1007/s13197-011-0290-7.
2. Barbosa-Cánovas, G. V. – Medina-Meza, I. – Candoğan, K. – Bermúdez-Aguirre, D.: Advanced retorting, microwave assisted thermal sterilization (MATS), and pressure assisted thermal sterilization (PATS) to process meat products. Meat Science, *98*, 2014, pp. 420–434. DOI: 10.1016/j.meatsci.2014.06.027.
3. Chemat, F. – Vian, M. A. – Fabiano-Tixier, A.-S. – Nutrizio, M. – Jambrak, A. R. – Munekata, P. E. – Lorenzo, J. M. – Barba, F. J. – Binello, A. – Cravotto, G.: A review of sustainable and intensified techniques for extraction of food and natural products. Green Chemistry, *22*, 2020, pp. 2325–2353. DOI: 10.1039/C9GC03878G.
4. Zhang, Z. – Li, X. – Tian, J. – Chen, J. – Gao, G.: A review: Application and research progress of bioimpedance in meat quality inspection. Journal of Food Process Engineering, *45*, 2022, article e14153. DOI: 10.1111/jfpe.14153.
5. Cheng, J.-H. – Sun, D.-W. – Qu, J.-H. – Pu, H.-B. – Zhang, X.-C. – Song, Z. – Chen, X. – Zhang, H.: Developing a multispectral imaging for simultaneous prediction of freshness indicators during chemical spoilage of grass carp fish fillet. Journal of Food Engineering, *182*, 2016, pp. 9–17. DOI: 10.1016/j.jfoodeng.2016.02.004.
6. Kamonpatana, P. – Sastry, S. K.: Electrical conductivity of foods and food components: The influence of formulation processes. Journal of Food Process Engineering, *45*, 2022, article e13992. DOI: 10.1111/jfpe.13992.
7. Kelkar, S. – Boushey, C. J. – Okos, M.: A method to determine the density of foods using X-ray imaging. Journal of Food Engineering, *159*, 2015, pp. 36–41. DOI: 10.1016/j.jfoodeng.2015.03.012.
8. Wang, H. – Hu, R. – Zhang, M. – Zhai, Z. – Zhang, R.: Identification of tomatoes with early decay using visible and near infrared hyperspectral imaging and image-spectrum merging technique. Journal of Food Process Engineering, *44*, 2021, article e13654. DOI: 10.1111/jfpe.13654.
9. Pliquett, U.: Bioimpedance: a review for food processing. Food Engineering Reviews, *2*, 2010, pp. 74–94. DOI: 10.1007/s12393-010-9019-z.
10. Zhang, Q. – Qu, M. – Liu, X. – Cui, Y. – Hu, H. – Li, Q. – Jin, M. – Xian, J. – Nie, Z. – Zhang, C.: Three-in-one portable electronic sensory system based on low-impedance laser-induced graphene on-skin electrode sensors for electrophysiological signal monitoring. Advanced Materials Interfaces, *10*, 2023, article 2201735. DOI: 10.1002/admi.202201735.
11. Qin, J. – Chao, K. – Kim, M. S. – Lu, R. – Burks, T. F.: Hyperspectral and multispectral imaging for evaluating food safety and quality. Journal of Food Engineering, *118*, 2013, pp. 157–171. DOI: 10.1016/j.jfoodeng.2013.04.001.
12. Zhao, X. – Zhuang, H. – Yoon, S. C. – Dong, Y. – Wang, W. – Zhao, W.: Electrical impedance spectroscopy for quality assessment of meat and fish: A review on basic principles, measurement methods, and recent advances. Journal of Food Quality, *2017*, 2017, article 6370739. DOI: 10.1155/2017/6370739.
13. Wu, D. – Shi, H. – He, Y. – Yu, X. – Bao, Y.: Potential of hyperspectral imaging and multivariate analysis for rapid and non-invasive detection of gelatin adulteration in prawn. Journal of Food Engineering, *119*, 2013, pp. 680–686. DOI: 10.1016/j.jfoodeng.2013.06.039.
14. Yang, B. – Guo, W. – Li, W. – Li, Q. – Liu, D. – Zhu, X.: Portable, visual, and nondestructive detector integrating Vis/NIR spectrometer for sugar content of kiwifruits. Journal of Food Process Engineering, *42*, 2019, article e12982. DOI: 10.1111/jfpe.12982.
15. Zhu, Z. – Yu, M. – Zhang, J. – Zhang, W.: Effects of ultrasonic-assisted curing on the eating quality of lamb. Journal of Food Engineering, *361*, 2024, article 111756. DOI: 10.1016/j.jfoodeng.2023.111756.
16. Balasubramanian, S. – Panigrahi, S. – Logue, C. M. – Gu, H. – Marchello, M.: Neural networks-integrated metal oxide-based artificial olfactory system for meat spoilage identification. Journal of Food Engineering, *91*, 2009, pp. 91–98. DOI: 10.1016/j.jfoodeng.2008.08.008.
17. Waters, C. W. – Varuzhanyan, G. – Talmadge, R. J. – Voss, A. A.: Huntington disease skeletal muscle is hyperexcitable owing to chloride and potassium channel dysfunction. Proceedings of the National Academy of Sciences, *110*, 2013, pp. 9160–9165. DOI: 10.1073/pnas.1220068110.
18. Alahakoon, A. – Oey, I. – Silcock, P. – Bremer, P.: Understanding the effect of pulsed electric fields on thermostability of connective tissue isolated from beef pectoralis muscle using a model system. Food Research International, *100*, 2017, pp. 261–267. DOI: 10.1016/j.foodres.2017.08.025.
19. Cheng, J. – Yu, P. – Huang, Y. – Zhang, G. – Lu, C. – Jiang, X.: Application status and prospect of impedance spectroscopy in agricultural product quality detection. Agriculture, *12*, 2022, article 1525. DOI: 10.3390/agriculture12101525.
20. Li, L. – Li, C. – Zhang, D. – Chen, L. – Li, S. – Wang, W. – Zheng, X.: A multiple parameters fusion model based on hydrogen sulfide for accurately evaluating the freshness of lamb meat. International Journal of Food Science and Technology, *58*, 2023, pp. 2921–2933. DOI: 10.1111/ijfs.16399.
21. Zhang, C. – Kong, J. – Wu, D. – Guan, Z. – Ding, B. – Chen, F.: Wearable sensor: an emerging data collection tool for plant phenotyping. Plant Phenomics, *5*, 2023, article 0051. DOI: 10.34133/plantphenomics.0051.
22. Wei, C. – Li, X.: A near-infrared spectroscopy method for the detection of texture profile analysis of Litopeneo vannamei based on partial least squares regression. Journal of Food Process Engineering, *45*, 2022, article e14140. DOI: 10.1111/jfpe.14140.
23. Jin, P. – Li, Z. – Zhang, X.: Freshness prediction of modified atmosphere packaging lamb meat based on digital images from mobile portable devices. Journal of Food Process Engineering, *46*, 2023, article e14444. DOI: 10.1111/jfpe.14444.
24. Sun, L. – Feng, S. – Chen, C. – Liu, X. – Cai, J.:

Identification of eggshell crack for hen egg and duck egg using correlation analysis based on acoustic resonance method. Journal of Food Process Engineering, *43*, 2020 article e13430. DOI: 10.1111/jfpe.13430.
25. Singha, P. – Muthukumarappan, K.: Effects of processing conditions on the system parameters during single screw extrusion of blend containing apple pomace. Journal of Food Process Engineering, *40*, 2017, article e12513. DOI: 10.1111/jfpe.12513.
26. Dalvi-Isfahan, M. – Havet, M. – Hamdami, N. – Le-Bail, A.: Recent advances of high voltage electric field technology and its application in food processing: A review with a focus on corona discharge and static electric field. Journal of Food Engineering, *353*, 2023, article 111551. DOI: 10.1016/j.jfoodeng.2023.111551.
27. Bera, T. K. – Nagaraju, J. – Lubineau, G.: Electrical impedance spectroscopy (EIS)-based evaluation of biological tissue phantoms to study multifrequency electrical impedance tomography (Mf-EIT) systems. Journal of Visualization, *19*, 2016, pp. 691–713. DOI: 10.1007/s12650-016-0351-0.
28. Chen, A. – Zeng, G. – Chen, G. – Liu, L. – Shang, C. – Hu, X. – Lu, L. – Chen, M. – Zhou, Y. – Zhang, Q.: Plasma membrane behaviour, oxidative damage, and defense mechanism in *Phanerochaete chrysosporium* under cadmium stress. Process Biochemistry, *49*, 2014, pp. 589–598. DOI: 10.1016/j.procbio.2014.01.014.
29. Damez, J.-L. – Clerjon, S.: Meat quality assessment using biophysical methods related to meat structure. Meat science, *80*, 2008, pp. 132–149. DOI: 10.1016/j.meatsci.2008.05.039.
30. Li, H. – Si, S. – Yang, K. – Mao, Z. – Sun, Y. – Cao, X. – Yu, H. – Zhang, J. – Ding, C. – Liang, H.: Hexafluoroisopropanol based silk fibroin coatings on AZ31 biometals with enhanced adhesion, corrosion resistance and biocompatibility. Progress in Organic Coatings, *184*, 2023, article 107881. DOI: 10.1016/j.porgcoat.2023.107881.
31. Huang, W. – Xia, J. – Wang, X. – Zhao, Q. – Zhang, M. – Zhang, X.: Improvement of non-destructive detection of lamb freshness based on dual-parameter flexible temperature-impedance sensor. Food Control, *153*, 2023, article 109963. DOI: 10.1016/j.foodcont.2023.109963.
32. Zhang, D. – Zhu, L. – Jiang, Q. – Ge, X. – Fang, Y. – Peng, J. – Liu, Y.: Real-time and rapid prediction of TVB-N of livestock and poultry meat at three depths for freshness evaluation using a portable fluorescent film sensor. Food Chemistry, *400*, 2023, article 134041. DOI: 10.1016/j.foodchem.2022.134041.
33. Fang, S. – Guan, Z. – Su, C. – Zhang, W. – Zhu, J. – Zheng, Y. – Li, H. – Zhao, P. – Liu, X.: Accurate fish-freshness prediction label based on red cabbage anthocyanins. Food Control, *138*, 2022, article 109018. DOI: 10.1016/j.foodcont.2022.109018.
34. Zhuang, Q. – Peng, Y. – Yang, D. – Nie, S. – Guo, Q. – Wang, Y. – Zhao, R.: UV-fluorescence imaging for real-time non-destructive monitoring of pork freshness. Food Chemistry, *396*, 2022, article 133673. DOI: 10.1016/j.foodchem.2022.133673.

Received 1 March 2023; 1st revised 24 April 2024; accepted 29 April 2024; published online 2 July 2024.