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A novel approach for determining coconut drink adulteration by means of laser light backscattering imaging

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ABSTRACT

In this work, the simulated adulteration of coconut drink by dilution with water was investigated using laser-light backscattering (LLB) imaging. The laser vision system consisted of six low power laser modules, emitting 1 mm diameter beams at wavelengths of 532, 635, 780, 808, 850 and 1,064 nm. The backscattering images were acquired by a grey scale camera with 12 bit resolution. Eight parameters were extracted to describe the backscattering profile. The methods of linear discriminant analysis (LDA) and partial least squares (PLS) regression were performed on LLB parameters for classifying and predicting dilution level of adulterated coconut drink samples. Based on the results, LLB signals responded sensitively to adulteration. LDA results showed that adulterated samples were correctly recognized with accuracies between 60 and 100%. PLS models were able to estimate the adulteration level of samples with coefficients of determination of 0.57–0.97 in validation. This result demonstrated the potential of laser-light backscattering imaging as a rapid and non-destructive optical technique for evaluation of coconut drink adulteration.

KEYWORDS

diffuse reflectance imaging, food quality control, non-destructive assessment

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INTRODUCTION

Food adulteration is a prohibited act to gain quick economic profit, in which the quality of original food is deliberately reduced by either adding inferior substances or removing valuable components (FDA, 2009). Adulteration can mislead the consumers about the quality of products (Aouadi et al., 2022; Bodor et al., 2023). Moreover, allergic reactions may occur, when consumers do not know the exact components of foods they are consuming. Every year, the economic damage caused by food adulteration was estimated to be around €30 billion for the global market (Steinberg et al., 2019) and €8 to €12 billion for the European market (European Commission, 2020).

Fruit-based drinks are rich in nutrients and bioactive substances, such as carbohydrates, proteins, vitamins, antioxidants and minerals. Among fruit-based beverages, coconut drink is known for not only its nutritional value but also as an isotonic drink thanks to its excellent rehydration index and blood glucose response (Intan Kailaku et al., 2015). Fruit-based beverages have become one of the most frequently adulterated foods because of their high market value. The practice of adulteration of fruit-based drinks is mainly performed through dilution with water, addition of sugar and food additives, and addition of less valuable juices; of which water dilution is the most common one because it is simple and inexpensive.

In order to protect the consumers from low quality beverages, numerous studies have been conducted to develop non-destructive techniques for detection of adulterated products. These methods can offer several advantages over chemical approaches, including quick data acquisition, no or less requirement for sample preparation, and environment protection (Soós et al., 2014; Vitális et al., 2020; Zaukuu et al., 2022). For instance, infrared (IR) spectroscopy was applied for quantifying addition of sugar to orange juice (Ellis et al., 2016), detecting artificial sweeteners in commercial fruit juices (Mabood et al., 2018), identifying exogenous carbohydrates in coconut water (Teklemariam et al., 2021), and classifying grape nectars adulterated with apple juice and cashew juice (Miaw et al., 2018). Sitorus et al. (2022) used mid-infrared spectroscopy in range of 4,000–16,702 nm for detecting adulteration of coconut milk with distilled water (Sitorus et al., 2022). In addition, a combination of electronic tongue and electronic nose was used to detect adulterants in tomato juices (Hong et al., 2014). Moreover, digital image analysis was applied to identify adulteration in *Physalis* juice (Licodiedoff et al., 2013), and orange juice (Stinco Scanarotti et al., 2014).

Among non-destructive approaches, LLB imaging is a novel technique for food quality control, which has found its application in determining quality attributes of fruits and crops during ripening and storage (Adebayo et al., 2017; Ali et al., 2017; Sanchez et al., 2020), detecting defects in fruits (Mollazade et al., 2017; Wu et al., 2020), monitoring quality parameters of fruits in postharvest processes (Hashim et al., 2013; Dénes et al., 2013). The principle of LLB imaging is based on the phenomenon of light backscattering that occurs when the light photons interact with internal components of food matrices and scatter back to the surface (Mollazade et al., 2012). The backscattering profile at the surface of food matrices is related to their quality attributes (Lu et al., 2006). Thus, measurement and analysis of the backscattering profile of foods could provide information about their quality.

LLB imaging was mainly used for quality evaluation of agricultural produces, its application on transparent or partially opaque materials is very limited. To the best of our knowledge, there is no literature on application of LLB imaging for detecting adulteration of coconut drinks. Thus, the main objective of this work aimed at investigating the applicability of laser light backscattering imaging technique for detection of adulterated coconut drink.

MATERIALS AND METHODS

Materials

Ready-to-serve coconut drink was purchased from the distributor SPAR Hungary Ltd. (Bicske, Hungary). The product ingredients mainly included water (92%), sugar, coconut milk (3%), and stabilizers. The samples were stored at room temperature (approximately 20 °C) before the experiment.

Simulation of adulteration

Simulation of adulteration of coconut drink was performed at five dilution levels by adding distilled water to the original coconut drink at 5% (v/v) increment to make five adulteration levels (0 as original drink, 5, 10, 15, and 20%).

Acquisition of laser backscattering images

The laser-induced diffuse reflectance system consisted of six low power laser modules, emitting 1 mm diameter beams at wavelengths of 532, 635, 780, 808, 850, and 1,064 nm. Direct reflectance was avoided by adjusting the incident angle of the light beam at 15°. Backscattering images were taken using a 12 bit camera (MV1-D1312, Photonfocus, Lachen, Switzerland) with 0.113 mm/pixel spatial resolution. To improve the signal-to-noise ratio and prevent the interference of environmental light during the measurement, image acquisition was conducted in a dark chamber. Figure 1 presents the setup of the vision system.

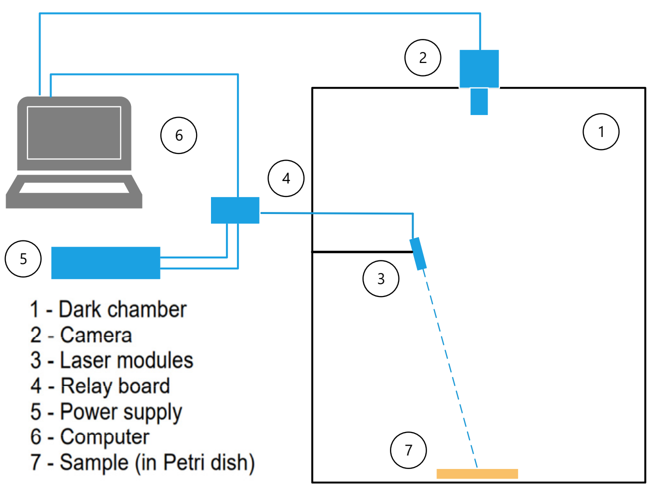

Fig. 1. Setup of the laser vision system

After being well stirred, samples were poured into a Petri dish with 3.5 mm height. For measurement of each adulteration level, three samples were used. Image acquisition of each sample was carried out using six laser light sources sequentially. Three images were captured for each wavelength and saved as binary image data. As a result, 18 images were obtained for each sample. The measurement of a sample lasted for less than 1 min; therefore, the result was not affected by sedimentation.

Method of image analysis

The captured images were processed using an algorithm, which was written in GNU Octave software (version 4.4.1). The binary images were converted to greyscale images (Fig. 2). Light intensity (0–4,095) was normalized to the range of 0–1. The 1 dimensional scattering profile was computed by averaging normalized intensity (Fig. 3). The LLB profile had a symmetric shape with highest intensity at the light incident point. As the distance from the incident point increased, the light intensity declined gradually. The LLB parameters were extracted (Fig. 4), including the peak widths at three selected intensity levels of 75%, 50%, 25% (D75, D50, D25); and the illuminated areas at selected intensity level of 50% (A50), the ring of 25–75 (A2575). The sharpness and the shape of the profile were described using the ratios of the widths (D25/D75, D50/D75) and the areas (A50/A2575).

Statistical analysis

Statistical analyses were performed using the free software R (version 4.2.1, R Foundation for Statistical Computing, Vienna, Austria) and RStudio (version 2023.06.1 + 524, Posit Software PBC, Boston, MA, USA). Two-way analysis of variance (ANOVA) was used to test significance of effects of adulteration and wavelength on LLB parameters ($P \leq 0.05$). Correlation analysis was performed to determine the relationship of LLB parameters and adulteration level. The classification ability of LLB imaging over adulterated samples was evaluated using linear discriminant analysis (LDA). The percentage of correctly classified data in validation was used to evaluate the

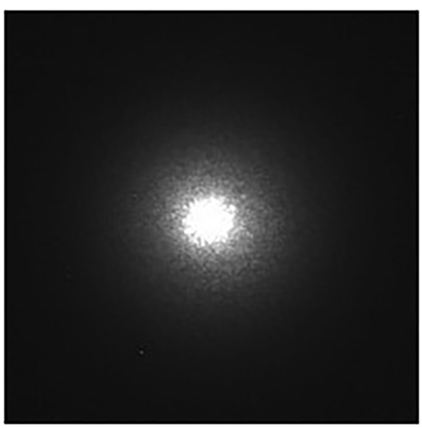

Fig. 2. Example of a backscattering image

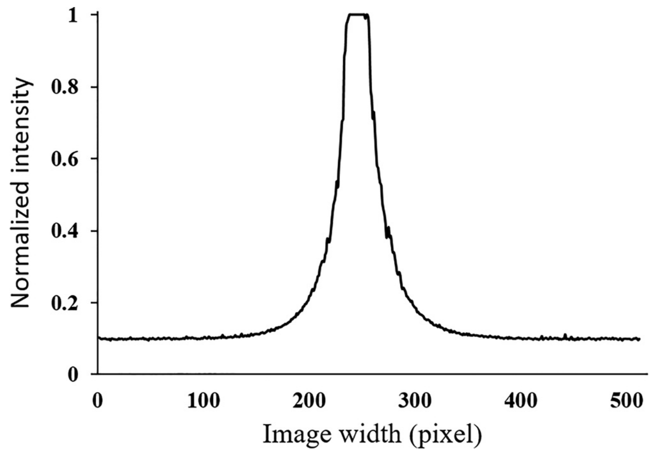

Fig. 3. 1 dimensional profile of LLB signal

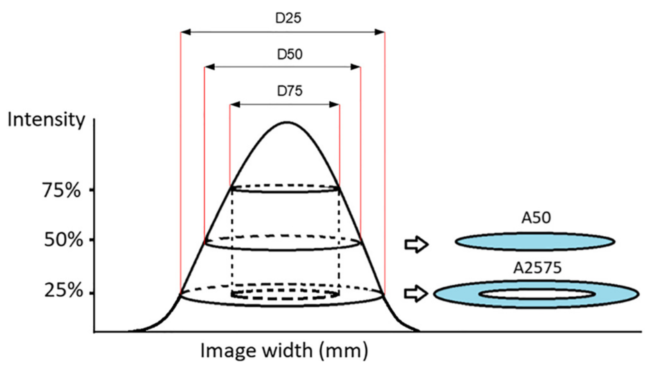

Fig. 4. Description of extracted backscattering parameters

classification power. Partial least squares (PLS) regression was used to predict the adulteration level. PLS model performance was evaluated based on coefficient of determination (R^2) and root mean squared error (RMSE) in validation. Both LDA and PLS models were trained using 80% randomly selected data and validated using the remaining 20% data.

RESULTS AND DISCUSSION

Change of LLB parameters

The significant changes of LLB parameters according to dilution level and wavelength were evaluated using two-way ANOVA at significance levels of $P < 0.05$ (Table 1). The result showed that adulteration had significant effects on parameters related to the peak widths and the illuminated areas of LLB profiles, including D75, D50, D25, A50, and A2575 ($P < 0.05$).

Table 1. ANOVA F-values of LLB parameters

Factor	LLB parameter	Mean Square	F	*P*
Wavelength	D75	319.65	100.61	<0.001
	D50	691.59	138.13	<0.001
	D25	2,606.53	184.99	<0.001
	D50/D75	0.06	2.86	<0.05
	D25/D75	0.95	9.74	<0.001
	A50	625,015.05	118.63	<0.001
	A2575	4,819,088.13	151.36	<0.001
	A50/A2575	0.03	35.48	<0.001
Dilution	D75	12.03	3.79	<0.05
	D50	29.22	5.84	<0.001
	D25	71.00	5.04	<0.001
	D50/D75	0.01	0.69	0.60
	D25/D75	0.07	0.70	0.60
	A50	27,483.43	5.22	<0.001
	A2575	201,112.93	6.32	<0.001
	A50/A2575	0.00	0.54	0.71
Wavelength × dilution	D75	2.92	0.92	0.57
	D50	4.95	0.99	0.49
	D25	9.17	0.65	0.85
	D50/D75	0.01	0.58	0.91
	D25/D75	0.07	0.67	0.84
	A50	5,130.78	0.97	0.51
	A2575	31,400.86	0.99	0.49
	A50/A2575	0.00	1.94	<0.05

Meanwhile, the parameters describing the sharpness and the shape of signals (D75/D25, D50/D25, A50/A2575) did not undergo any significant changes ($P > 0.05$). Significant variation of LLB signals by wavelength was also observed. D25 ($F = 184.99$) and A2575 ($F = 151.36$) were the most sensitive parameters to wavelength, whereas the two ratios of D50/D75 ($F = 2.86$) and D25/D75 ($F = 9.74$) had the lowest response. Furthermore, all parameters showed no significant interaction effects of factors ($P > 0.05$), except the ratio A50/A2575 ($P < 0.05$).

The relationship of measured backscattering signals and adulteration level was explored using correlation analysis (Table 2). The parameters for the widths and areas of profile (D75, D50, D25, A50, and A2575) had stronger correlation with adulteration level than their ratios (D25/D75, D50/D75, and A50/A2575). The strongest correlations were observed for A50 and A2575 at 635, 780, 808, 850, and 1,064 nm with absolute values of correlation coefficient up to 0.96. As a colloidal system with oil-in-water emulsion, the coconut drink contains fat droplets which mainly scatter the light. In diluted samples, the reduction in concentration of fat can be the reason for the change in light backscattering. This assumption is supported by Qin et al. (2007), who observed a correlation of reduced scattering coefficient and fat content of milk (Qin et al., 2007). Additionally, according to Mie's scattering theory, the scattering intensity is correlated to the refractive index ratio between scattering particles and liquids surrounding the particles (Mie, 1908). In this work, the addition of water to coconut drink samples changed their refractive indices, thus varying the light scattering.

Table 2. Correlation coefficient of LLB parameters and adulteration level

LLB parameter	Wavelength					
	532 nm	635 nm	780 nm	808 nm	850 nm	1,064 nm
D75	−0.22	−0.8	−0.85	−0.61	−0.17	−0.47
D50	−0.25	−0.84	−0.75	−0.6	−0.63	−0.57
D25	−0.1	−0.77	−0.59	−0.6	−0.79	−0.78
A50	−0.3	−0.95	−0.96	−0.9	−0.62	−0.46
A2575	−0.08	−0.94	−0.90	−0.9	−0.91	−0.92
D50/D75	−0.06	0.22	0.16	−0.02	−0.44	0.11
D25/D75	0.18	0.49	0.03	−0.14	−0.45	0.2
A50/A2575	−0.71	−0.81	0.55	0.08	0.48	0.27

Based on the above findings, it can be concluded that LLB parameters had high responses to adulteration and this proposed technique is promising for detecting adulteration in studied coconut drink.

Detection of adulteration

In this work, the feasibility of LLB imaging for detection of adulteration in coconut drink was investigated using the methods of LDA and PLS regression. LDA and PLS models were built using LLB parameters of single wavelength (8 parameters per wavelength) and their combination of all six wavelengths (48 parameters). All models were trained using 80% randomly selected data and validated using the remaining 20%. The quality of models was evaluated using calculated metrics in validation.

For classification, Table 3 illustrates the average accuracy of LDA models. Based on the result, LDA models of 635, 780, 808, 850, 1,064 nm achieved good accuracy of 80%. Meanwhile, the LDA model of 532 nm performed with the lowest success rate of 60%. The highest classification power was observed for the LDA model of all wavelengths with the accuracy of 100%. Regarding adulteration level quantification, the performance of PLS models is given in Table 4. The number of latent variables (LV) varied in range of 2–3, which was determined at minimum values of RMSE. In general, PLS models achieved $R^2 = 0.57 – 0.97$ and RMSE = 0.309 – 1.651%. The quality of a model is considered excellent when its coefficient of determination is greater than 0.90 (Cuadrado et al., 2005). For single wavelength, the best performances of the PLS model

Table 3. Performance of LDA classification

Wavelength	Classification accuracy
532 nm	60%
635 nm	80%
780 nm	80%
808 nm	80%
850 nm	80%
1,064 nm	80%
All wavelengths	100%

Table 4. Performance of PLS models

Wavelength	LV	R^2	RMSE (%)
532 nm	2	0.57	1.651
635 nm	2	0.81	0.309
780 nm	2	0.90	0.458
808 nm	2	0.81	0.479
850 nm	2	0.83	0.494
1,064 nm	2	0.93	0.545
All wavelengths	3	0.97	0.352

were observed at 780 nm (R^2 = 0.90, RMSE = 0.458%) and 1,064 nm (R^2 = 0.93, RMSE = 0.545%). Meanwhile, the PLS model at 532 nm was not appropriate for determination of adulteration level due to its poor performance (R^2 = 0.57, RMSE = 1.651%). Similar to LDA classification, the use of multispectral data with combination of all wavelengths resulted in an increase of PLS model accuracy with R^2 = 0.97 and RMSE = 0.352%.

Our findings demonstrated that LLB imaging is capable of identifying adulteration by water addition in coconut drink used in present study. The proposed technique achieved similar performance with the mid-infrared spectroscopy (4,000–16,702 nm), applied by Sitorus et al. (2022) for predicting adulteration level in water-adulterated coconut milk. Their PLS model obtained high accuracy of prediction with R^2 > 0.90 and RMSE <2% (Sitorus et al., 2022). For adulteration detection in transparent and partially opaque products, application of LLB imaging is very limited. Recently, a very first research was performed by Hencz et al. (2022) who investigated the feasibility of LLB imaging in detecting adulterants in red and white wines (Hencz et al., 2022). For detection of water dilution, their LDA models (success rate ≤76.67%) obtained poorer accuracy than ours. Moreover, the prediction error of their general linear model (20.39%) was much higher than that of our PLS models (<2%). The results of this work suggest that the proposed method can be used for adulteration detection of coconut drink.

CONCLUSION

The applicability of LLB imaging for detection of coconut drink adulteration was confirmed. The results of LDA showed that the proposed technique was able to recognize the diluted coconut drink used in the present work. All LDA models obtained high accuracy of discrimination with success rate up to 100%. LDA model produced no misclassification in combination of all wavelengths. PLS models obtained high performance with R^2 > 0.80 and RMSE <1% using backscattering signals at single wavelengths of 635, 780, 808, 850 and 1,064 nm. The quality of the PLS model was improved when signals of all wavelengths were used (R^2 = 0.97, RMSE = 0.352%). Based on the results, we suggest multispectral measurement in detection of adulteration with a combination of 532, 635, 780, 808, 850, 1,064 nm. However, our work has a limitation since its findings are based on the measurement of a small sample from one manufacturer. More studies are needed with larger samples to demonstrate the promising application of the technique in real life.

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REFERENCES

Adebayo, S.E., Hashim, N., Hass, R., Reich, O., Regen, C., Münzberg, M., and Zude-Sasse, M. (2017). Using absorption and reduced scattering coefficients for non-destructive analyses of fruit flesh firmness and soluble solids content in pear (Pyrus communis 'Conference')—an update when using diffusion theory. *Postharvest Biology and Technology*, 130: 56–63. https://doi.org/10.1016/j.postharvbio.2017.04.004.

Ali, M.M., Hashim, N., Bejo, S.K., and Shamsudin, R. (2017). Laser-induced backscattering imaging for classification of seeded and seedless watermelons. *Computers and Electronics in Agriculture*, 140: 311–316. https://doi.org/10.1016/j.compag.2017.06.010.

Aouadi, B., Vitalis, F., Bodor, Z., Zinia Zaukuu, J.-L., Kertesz, I., and Kovacs, Z. (2022). NIRS and aquaphotomics trace Robusta-to-Arabica ratio in liquid coffee blends. *Molecules*, 27(2): 388. https://doi.org/10.3390/molecules27020388.

Bodor, Z., Majadi, M., Benedek, C., Zaukuu, J.-L.Z., Veresné Bálint, M., Csajbókné Csobod, É., and Kovacs, Z. (2023). Detection of low-level adulteration of Hungarian honey using near infrared spectroscopy. *Chemosensors*, 11(2): 89. https://doi.org/10.3390/chemosensors11020089.

Cuadrado, M.U., De Castro, M.L., Juan, P.P., and Gómez-Nieto, M. (2005). Comparison and joint use of near infrared spectroscopy and Fourier transform mid infrared spectroscopy for the determination of wine parameters. *Talanta*, 66(1): 218–224. https://doi.org/10.1016/j.talanta.2004.11.011.

Dénes, L.D., Parrag, V., Felföldi, J., and Baranyai, L. (2013). Influence of parameters of drying on laser induced diffuse reflectance of banana discs. *Journal of Food Physics*, 26(1): 11–16.

Ellis, D.I., Ellis, J., Muhamadali, H., Xu, Y., Horn, A.B., and Goodacre, R. (2016). Rapid, high-throughput, and quantitative determination of orange juice adulteration by Fourier-transform infrared spectroscopy. *Analytical Methods*, 8(28): 5581–5586. https://doi.org/10.1039/C6AY01480A.

European Commission (2020). *Food fraud*, Available online: https://knowledge4policy.ec.europa.eu/food-fraud-quality/topic/food-fraud_en (Accessed on 25 October 2023).

FDA (2009). Economically motivated adulteration; public meeting; request for comment. [Electronic version]. *Fed Register*, 74(64): 15497–15499.

Hashim, N., Pflanz, M., Regen, C., Janius, R.B., Rahman, R.A., Osman, A., and Zude, M. (2013). An approach for monitoring the chilling injury appearance in bananas by means of backscattering imaging. *Journal of Food Engineering*, 116(1): 28–36. https://doi.org/10.1016/j.jfoodeng.2012.11.018.

Hencz, A., Nguyen, L.L.P., Baranyai, L., and Albanese, D. (2022). Assessment of wine adulteration using near infrared spectroscopy and laser backscattering imaging. *Processes*, 10(1): 95. https://doi.org/10.3390/pr10010095.

Hong, X., Wang, J., and Qiu, S. (2014). Authenticating cherry tomato juices—discussion of different data standardization and fusion approaches based on electronic nose and tongue. *Food Research International*, 60: 173–179. https://doi.org/10.1016/j.foodres.2013.10.039.

Intan Kailaku, S., Nur Alam Syah, A., Risfaheri, R., Setiawan, B., and Sulaeman, A. (2015). Carbohydrate-electrolyte characteristics of coconut water from different varieties and its potential as natural isotonic drink. *International Journal on Advanced Science, Engineering and Information Technology*, 5(3): 174–177.

Licodiedoff, S., Ribani, R.H., Camlofski, A.M.d.O., and Lenzi, M.K. (2013). Use of image analysis for monitoring the dilution of Physalis peruviana pulp. *Brazilian Archives of Biology and Technology*, 56: 467–474. https://doi.org/10.1590/S1516-89132013000300015.

Lu, R. and Peng, Y. (2006). Hyperspectral scattering for assessing peach fruit firmness. *Biosystems engineering*, 93(2): 161–171. https://doi.org/10.1016/j.biosystemseng.2005.11.004.

Mabood, F., Hussain, J., Jabeen, F., Abbas, G., Allaham, B., Albroumi, M., and Al-Harrasi, A. (2018). Applications of FT-NIRS combined with PLS multivariate methods for the detection & quantification of saccharin adulteration in commercial fruit juices. *Food Additives & Contaminants: Part A*, 35(6): 1052–1060. https://doi.org/10.1080/19440049.2018.1457802.

Miaw, C.S.W., Sena, M.M., de Souza, S.V.C., Callao, M.P., and Ruisanchez, I. (2018). Detection of adulterants in grape nectars by attenuated total reflectance Fourier-transform mid-infrared spectroscopy and multivariate classification strategies. *Food Chemistry*, 266: 254–261. https://doi.org/10.1016/j.foodchem.2018.06.006.

Mie, G. (1908). Beitrage Zur Optik Trüber Medien, Speziell Kolloidaler Metallosungen. *Annalen der Physik*, 330: 377–445.

Mollazade, K. and Arefi, A. (2017). Optical analysis using monochromatic imaging-based spatially-resolved technique capable of detecting mealiness in apple fruit. *Scientia Horticulturae*, 225: 589–598. https://doi.org/10.1016/j.scienta.2017.08.005.

Mollazade, K., Omid, M., Tab, F.A., and Mohtasebi, S.S. (2012). Principles and applications of light backscattering imaging in quality evaluation of agro-food products: a review. *Food and Bioprocess Technology*, 5: 1465–1485. https://doi.org/10.1007/s11947-012-0821-x.

Qin, J. and Lu, R. (2007). Measurement of the absorption and scattering properties of turbid liquid foods using hyperspectral imaging. *Applied spectroscopy*, 61(4): 388–396.

Sanchez, P.D.C., Hashim, N., Shamsudin, R., and Nor, M.Z.M. (2020). Laser-light backscattering imaging approach in monitoring and classifying the quality changes of sweet potatoes under different storage conditions. *Postharvest Biology and Technology*, 164: 111163. https://doi.org/10.1016/j.postharvbio.2020.111163.

Sitorus, A. and Bulan, R. (2022). Development of a screening method for adulteration detection in coconut milk via mid-infrared spectroscopy: a study of linear and nonlinear regression method. *Journal of Agriculture and Food Research*, 10: 100438. https://doi.org/10.1016/j.jafr.2022.100438.

Soós, J., Várvölgyi, E., Dénes, L., Kovács, Z., Felföldi, J., and Magyar, I. (2014). Application of electronic tongue to discriminate white wines originated from different regions of Hungary. *Acta Alimentaria*, 43(Supplement-1): 132–139. https://doi.org/10.1556/aalim.43.2014.suppl.19.

Steinberg, P. and Engert, S. (2019). A daring task: the battle against food crime. *Journal of Consumer Protection and Food Safety*, 14: 317–318. https://doi.org/10.1007/s00003-019-01259-9.

Stinco Scanarotti, C.M., Fernández Vázquez, R., Heredia Mira, F.J., Meléndez Martínez, A.J., and Vicario Romero, I. (2014). Spectroradiometry vs. digital image analysis in colour measurement in juices from different orange and Mandarin varieties. *Óptica pura y aplicada*, 47(2): 139–144. https://doi.org/10.7149/OPA.47.2.139.

Teklemariam, T.A., Moisey, J., and Gotera, J. (2021). Attenuated Total Reflectance-Fourier transform infrared spectroscopy coupled with chemometrics for the rapid detection of coconut water adulteration. *Food Chemistry*, 355: 129616. https://doi.org/10.1016/j.foodchem.2021.129616.

Vitális, F., Zaukuu, J.L.Z., Bodor, Z., Aouadi, B., Hitka, G., Kaszab, T., and Kovacs, Z. (2020). Detection and quantification of tomato paste adulteration using conventional and rapid analytical methods. *Sensors*, 20(21): 6059. https://doi.org/10.3390/s20216059.

Wu, A., Zhu, J., and Ren, T. (2020). Detection of apple defect using laser-induced light backscattering imaging and convolutional neural network. *Computers & Electrical Engineering*, 81: 106454. https://doi.org/10.1016/j.compeleceng.2019.106454.

Zaukuu, J.-L.Z., Benes, E., Bázár, G., Kovács, Z., and Fodor, M. (2022). Agricultural potentials of molecular spectroscopy and advances for food authentication: an overview. *Processes*, 10(2): 214. https://doi.org/10.3390/pr10020214.