A COMPREHENSIVE OVERVIEW OF NEAR INFRARED AND INFRARED SPECTROSCOPY FOR DETECTING THE ADULTERATION ON FOOD AND AGRO-PRODUCTS—A CRITICAL ASSESSMENT
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TINJAUAN KOMPREHENSIF SPEKTROSKOPI INFRAMERAH DEKAT DAN INFRAMERAH UNTUK MENDETEKSI PEMALSUAN PADA MAKANAN DAN PRODUK PERTANIAN—PENILAIAN KRITIS

Agustami SITORUS [1, 2], Ravipat LAPCHAROENSUK *[1],

[1] Department of Agricultural Engineering, School of Engineering, King Mongkut's Institute of Technology Ladkrabang, Thailand

[2] Research Centre for Appropriate Technology, National Research and Innovation Agency / Indonesia

Tel: +62 812-8343-9334; E-mail: ravipat.la@kmitl.ac.th

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ABSTRACT
In the past decade, fast and non-destructive methods based on spectroscopy technology have been studied to detect and discriminate against food adulteration and agro-products. Numerous linear and nonlinear chemometric approaches have been developed for spectroscopy analysis. Recently, various approaches have been developed for spectroscopic calibration modelling to detect and discriminate adulteration food and agro-products. This article discusses the application of spectroscopy technology, including near infrared and infrared, in detecting and discriminating the adulteration of food and agro-products based on recent research and delivered a critical assessment on this topic to serve as lessons from current studies and future outlooks. The current state-of-the-art techniques, including detection and classification of various adulteration in food and agro-products, have been addressed in this paper. Key findings from this study, near infrared and infrared spectroscopy is a non-destructive, rapid, simple-preparation, analytical rapidity, and straightforward method for classification and determination of adulteration in the food and agro-products so it is suitable for large-scale screening and on-site detection. Although there are still some unsatisfactory research results, especially in detecting tiny adductors, these technologies can potentially detect any adulteration in the various food and agro-products at an economically viable level, at least for the initial screening process. In that respect, near infrared and infrared spectroscopy should be expanded to cover all food and agro-products sold in the market. Only then will there be an acceptable deterrent in place to stop adulteration activity in widely consumed food and agro-products ingredients.

ABSTRAK
Dalam satu dekade terakhir, metode cepat dan non-destruktif berdasarkan teknologi spektroskopi telah banyak dipelajari untuk mendeteksi dan membedakan pemalsuan produk makanan dan pertanian. Banyak pendekatan kemometrik linier dan nonlinier telah dikembangkan untuk analisis spektroskopi. Baru-baru ini, berbagai pendekatan telah dikembangkan juga untuk pemodelan kalibrasi spektroskopi dalam mendeteksi dan membedakan pemalsuan produk makanan dan pertanian. Artikel ini membahas penerapan teknologi spektroskopi, termasuk inframerah dekat dan inframerah, dalam mendeteksi dan membedakan pemalsuan produk makanan dan pertanian berdasarkan penelitian terbaru dan menyampaikan penilaian kritis tentang topik ini untuk dijadikan pelajaran dari studi saat ini dan pandangan dimasa depan. Teknik mutakhir saat ini, termasuk deteksi dan klasifikasi berbagai pemalsuan dalam produk makanan dan pertanian, telah dibahas dalam makalah ini. Temuan utama dari penelitian ini, spektroskopi inframerah dekat dan inframerah adalah metode non-destruktif, cepat, sederhana, kecepatan analitis, dan metode yang mudah untuk klasifikasi dan penentuan pemalsuan dalam produk makanan dan pertanian sehingga cocok untuk skala besar, penyaringan dan deteksi di tempat. Meskipun masih ada beberapa hasil penelitian yang tidak memuaskan, terutama dalam mendeteksi adduktor kecil, teknologi ini berpotensi mendeteksi pemalsuan dalam berbagai produk makanan dan pertanian pada tingkat yang layak secara ekonomi, setidaknya untuk proses penyaringan awal. Dalam hal ini, spektroskopi inframerah dekat dan inframerah harus diperluas untuk mencakup semua produk makanan dan pertanian yang dijual di pasar. Hanya dengan demikian akan ada pencegah yang dapat diterima untuk menghentikan aktivitas pemalsuan bahan makanan dan produk pertanian yang dikonsumsi secara luas.

INTRODUCTION

In today's worldwide economy, concerns about food authenticity are a top priority. Customers' primary focus has changed to the originality of food and agro-products commodities, due to the growing desire for local products (*Amirvaresi et al.*, 2021; *Wongsaipun et al.*, 2021; *Tao et al.*, 2021). As a result, indigenous food and agro-products are frequently chosen over imported ones. Consumers consider freshness and geographical origin when selecting high-quality food products to consume daily, such as meat, flour, flavouring, herbs, and spices.

The increasing population and high cost of produced food and agro-products have created opportunities to use adulteration in postharvest processing. The quality control of these products still relies on laboratory testing based on chemical analysis. Regrettably, these methods seem expensive, complicated to use, usually time-consuming and require a sample preparation step before analysis, in turn, they need many kinds of chemical solvent. In that respect, the option of spectroscopy technology, including near infrared and infrared, offers a valid key to overcoming some of the abovementioned disadvantages since they allow performing a non-destructive evaluation, rapid, easy, eco-friendly, and directly in situ (*Galvin-King et al.*, 2021a; *Silva et al.*, 2020; *Ndlovu et al.*, 2019). This is why researchers have worked over the years to find another application as standard analysis in various fields, especially food science (*Ozaki et al.*, 2021).

According to the recent literature, many studies have been using spectroscopy technology, including near infrared and infrared, to detect and classify the adulteration of food and agro-products. Yet, to date, no comprehensive study has reported on it or provided a critical assessment on this topic. Therefore, the article presents an overview of the application of near infrared and infrared spectroscopy in detecting and discriminating the adulteration of food and agro-products based on recent research.

METHODS

Applications of spectroscopy technology, including near infrared and infrared, to assess fraud, particularly in food and agro-products, have increased each year (Fig. 1). Research papers were searched in February 2022 via the electronic database Scopus (www.scopus.com). The keyword for finding the research papers using “NIR” or “near-infrared” and “adulteration”. From the first search, research papers can be categorized into an article (447), conference article (56), review (41), book chapter (15), conference review (5) and short survey (1). Most of the articles published come from China (33.6%), followed by Brazil (11.7%), the United States (8.3%), Spain (6.2%), the UK (4.8%), India (4.4%), Italy (4.2%), Ireland (4.1%), Malaysia (3.2%), and France (3.0%). The most popular keywords were infrared device (50.4%), near infrared spectroscopy (50.4%), adulteration (29.9%), least squares approximations (23.7%), chemometrics (20.4%), principal component analysis (19.6%), and spectroscopy, near infrared (18.8%).

Subsequently, the abstracts of the paper were investigated to include or exclude them in this article. From there, 447 documents were further examined, and inappropriate documents were excluded. Excluded research papers were carried out because they did not use near infrared or infrared spectroscopy to detect adulteration, papers that did not use food and agro-products as the main object of the study, conference papers, book chapters, conference reviews, short survey, and review articles. A total of 126 documents were used in the further study. An overview of the research papers is shown in Table 1 to Table 3.

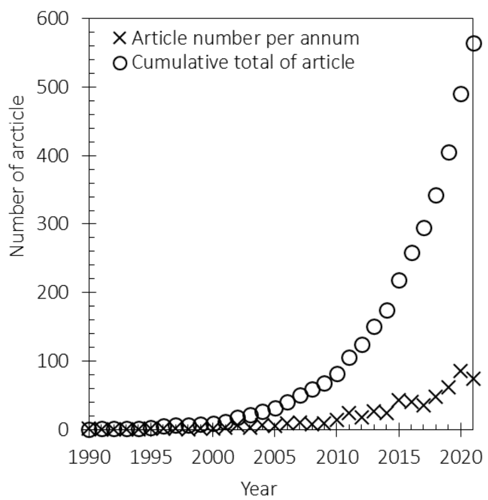

Fig. 1 – Metadata Scopus record of research paper per annum and cumulative total of articles until 2021

NEAR INFRARED AND INFRARED SPECTROSCOPY FOR FOOD AND AGRO-PRODUCT

Infrared (IR) spectroscopy uses the spectral range between 800 and 500000 nm, which can be further subdivided into the far IR (FIR: 25000 to 500000 nm), the mid IR (MIR: 2500 to 25000 nm), the near IR (NIR: 800 to 2500 nm), and ultraviolet-visible (UV-VIS: 200 to 780) (*Reich*, 2016; *Ozaki et al.*, 2021). The application of near infrared and infrared spectroscopy for food and agro-products has long been known in the industrial world and continues to expand today (*Wesley et al.*, 1995). In general, this technology is utilized to evaluate food and agro-products in the form of quantitative and qualitative analysis. The wavelengths used vary widely from near infrared spectroscopy (780–2500 nm) to MIR spectroscopy (2500–25000 nm) (*Santos et al.*, 2021; *Alamar et al.*, 2020; *Pereira et al.*, 2019). Meanwhile, some researchers combine the wavelength of the near infrared spectroscopy region with the wavelength of the visible region wavelength (340–2500 nm) or commonly known as VIS-NIR spectroscopy (*Pandiselvam et al.*, 2022; *Valinger et al.*, 2021b; *Ndlovu et al.*, 2021b).

Likewise, several wavelength ranges in near infrared and infrared spectroscopy for food and agro-products that have been studied are shown in Fig. 2. Unfortunately, although it has limitations in the spectral range, visible near infrared technology (340–780 nm) is still used to detect and discriminate adulteration in food and agro-products. However, full-wavelength near infrared (780–2500 nm) and infrared (2500–16000 nm) spectroscopy with wider wavelengths are more commonly used for detecting adulterations of food and agro-products. On the other hand, some studies also combine ultraviolet, visible, and near infrared wavelength ranges known as UV-VIS-NIR (325–2500 nm).

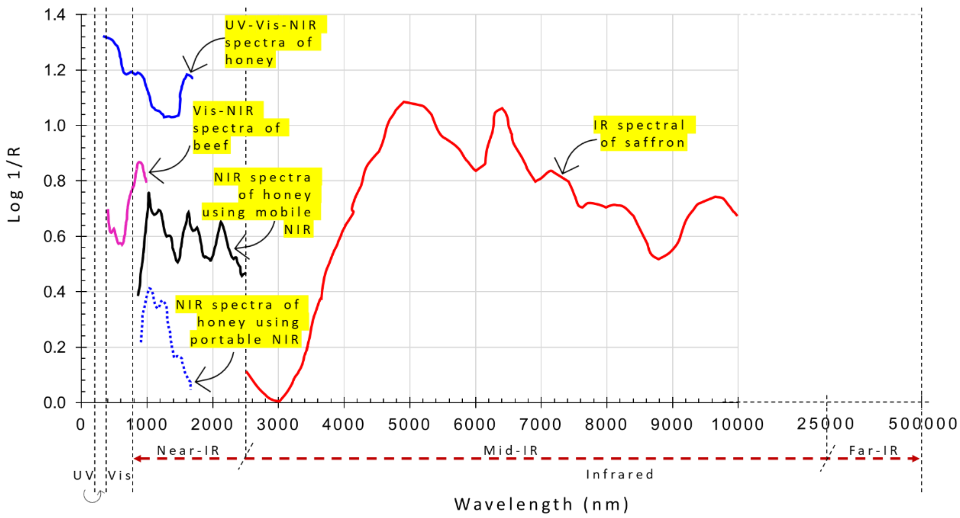

Fig. 2 – Wavelength range of near infrared and infrared spectroscopy technology

Near infrared spectroscopy technology (780–2500 nm)

The spectral band represents the interaction of molecules with the near infrared wavelength. The chemical content on the samples tends to absorb specific frequencies of light when a sample is irradiated with near infrared spectroscopy. Thus, near infrared spectroscopy can provide a fingerprint of the content in a sample, especially in food and agro-products. Near infrared spectroscopy has been used in a wide range of investigations to find adulteration in foods and agro-products such as livestock (*dos Santos Pereira et al.*, 2021a; *Teixeira et al.*, 2021a; *Mabood et al.*, 2020), flour (*Ndlovu et al.*, 2021a; *Ayvaz et al.*, 2021b; *Tao et al.*, 2021), liquid agro-product (*Tan et al.*, 2021; *Valinger et al.*, 2021b; *Du et al.*, 2021b), and herbs and spices (*Castro et al.*, 2021; *Cantarelli et al.*, 2020; *Rukundo and Danao*, 2020).

Near infrared spectroscopy offers a fast, effective, and low-cost alternative procedure that can provide clues about the chemical content and physical properties of the samples. The more affordable near infrared spectroscopy technology is due to the fact that more and more mechatronic industries are developing spectrometer packages that are simpler, more portable, and smaller in size than the benchtop types available in the laboratory.

Several studies have reported that it detects adulteration in food and agro-products using portable near infrared spectroscopy in the wavelength range of 908–1676 nm, 950–1650 nm, 1351-2551 nm and 1600–2400 nm (*dos Santos Pereira et al.*, 2021b; *Oliveira et al.*, 2020; *Aykas and Menevseoglu*, 2021; *Correia et al.*, 2018; *Silva et al.*, 2020; *Torres et al.*, 2021; *Santos et al.*, 2013). Although many industries have developed near infrared spectroscopy technology packages, unfortunately, they will still be relatively expensive over the next few years. On the other hand, near infrared spectroscopy instruments generate a large amount of data that require an adequate method to build useful analytical information. Combining chemometric and near infrared spectroscopy techniques is required to collect as much associated information from the spectral data as possible (*Genis et al.*, 2021). In this case, chemometrics is the science of extracting information from a chemical system through data-driven methods.

The use of a wider spectral region allowed them to obtain more information related to the stretching and deformation vibrations of the C–H, O–H, and N–H groups that are abundant in a sample. For example, from a honey sample, wavelengths in the visible region up to near infrared (400–2500 nm) are related to those compounds in the honey that absorb in the blue-violet range, giving the characteristic orange-amber color of the honey (*Yang et al.*, 2020). In the near infrared region, the wavelength at 1451 nm is related to the first overtone of the vibrational mode of the O–H stretch from water (*Huang et al.*, 2020a). Therefore, signal regions of near-infrared and infrared spectra are needed to understand the compound in the samples with greater precision. With that in mind, the next step is to focus only on the few wavelength regions that can provide the information that correlates with the compounds in our sample. In addition, portable near infrared spectroscopy with a narrow wavelength region can be utilized, while providing high accuracy.

Infrared spectroscopy technology (2500–16000 nm)

Infrared spectroscopy data cover the 2500 to 16000 nm range used to represent fundamental vibrations, molecular overtones, and combination vibrations. The absorption areas are predominantly composed of hydrogen-containing groups related to the acid, oil content, protein, sugar, and water of food and agro-products. Consequently, the spectral contains chemical information by reflecting the molecular structures from the samples.

Several recent studies have been carried out using infrared spectroscopy technology to detect and discriminate adulteration of food and agricultural products for livestock products, including milk and eggs (*Hosseini et al.*, 2021; *Botelho et al.*, 2015; *Uysal and Boyaci*, 2020). In addition, flour products have been investigated for products including pistachios and peppers (*Aykas and Menevseoglu*, 2021; *Galvin-King et al.*, 2020a). Liquid products have also been studied for products including yogurt, guava pulp, durum wheat pasta, and butter oil (*Temizkan et al.*, 2020b; *Alamar et al.*, 2020; *De Girolamo et al.*, 2020b; *Pereira et al.*, 2019). For herbs and spices, products have been studied, including those of black pepper, garlic, and saffron (*Wilde et al.*, 2019; *Galvin-King et al.*, 2021a; *Amirvaresi et al.*, 2021). Nevertheless, the most challenging thing for researchers in adulteration studies in this range spectral is to explain the connection between absorption in the spectral region with the chemical content of food and agro-products. Occasionally, the various intrinsic properties to be determined usually lead to non-linear patterns. Finally, many linear and non-linear chemometric approaches have been developed for quantitative and qualitative analyses to tackle this problem.

ANALYSIS DATA

Spectral data analysis is the most important part of obtaining the information contained therein. In general, the procedure that must be followed in extracting the information in the near infrared and infrared spectra, especially related to the purity of food and agro-products, is presented in Fig. 3. Food and agro-products that have been adulterated with an adulterating agent will create different infrared spectra data as a result of the various functional groups in the material. However, this will not necessarily produce information without developing a calibration model, which is followed by testing to build a predictive model. Furthermore, the predictive model performance should also be tested with several unknown datasets to create a proven model.

In many cases of adulteration of food and agro-products, the processing and pre-treatment steps are very important to reduce noise spectra data. Furthermore, many linear and nonlinear chemometric approaches, including Partial Least Squares Regression (PLSR), Principal Component Regression (PCR), Support Vector Machine (SVM), and Artificial Neural Network (ANN), have been developed to quantify the physical and chemical properties of food and agricultural products to acquire information from spectral data. The last two algorithms are the newest, along with the k-nearest neighbour (k-NN), the Convolutional Neural Network (CNN), and the Radial Basis Function Neural Networks (RBFNN) based on machine learning, which are reported to produce the best predictive models compared to PLSR and PCR (*Xie et al.*, 2008; *Alamar et al.*, 2020; *Liu et al.*, 2021).

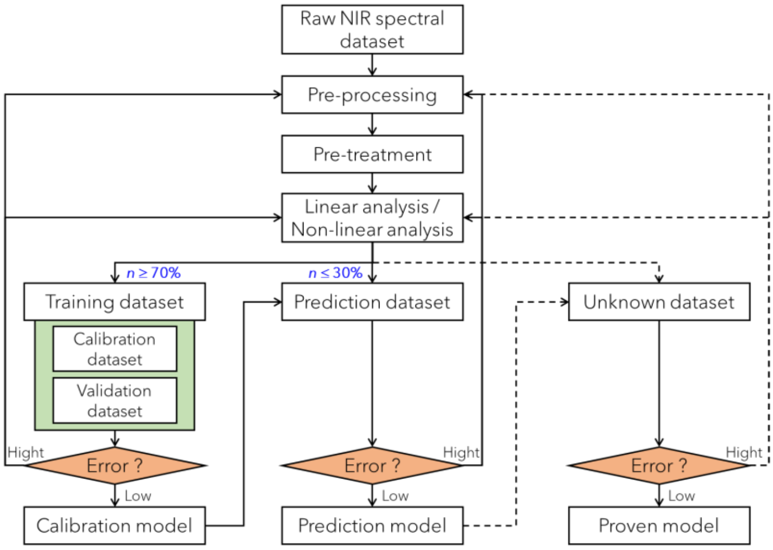

Fig. 3 – Procedure of model construction and performance evaluation

Pre-processing data

The difficulty of using spectral data for food and agro-products quality assessment stems from the need for a strong and accurate model with low sensitivity and low-intensity spectral data. Almost all studies involving near infrared and infrared spectroscopy use pre-processing data to avoid noise from light scattering, instrumental drift, particle size variation, and also high overlaps between combination bands and overtones to address this problem. Pre-processing is a method used to go from raw data to clean data ready for analysis including removing baseline artifacts, peak selection, or alignment. Pre-treatment is to transform the pre-processed data to make them suitable for analysis, including normalization, scaling, transformations, and removing any outliers in the data.

The application of pre-processing does not always provide the best results. For example, *Valinger et al.* (2021b) did not apply pre-processing or pre-treatment to its spectral data. However, they could provide an RPD value greater than 3 using the PLSR algorithm to detect fructose corn in honey. However, *Santos et al.* (2021) reported that pre-processing of SNV to detect adulteration of cocoa solids gave better results than without the application of pre-processing. Therefore, we conclude that applying pre-processing to near infrared and infrared spectroscopy data is a procedure that must be tested regardless of the results obtained.

Linear approach

A linear approach in near infrared and infrared spectroscopy data analysis will be successful if a linear association exists between the absorbance spectra and predicted content, more commonly referred to as the Beer-Lambert law. It is capable of conducting qualitative and quantitative analyses of adulteration in food and agro-products. The linear chemometric methods that were used most frequently to formulate a qualitative and quantitative analysis of adulteration in food and agro-products were PLSR, PCR, Partial Least Squares Discriminant Analysis (PLS-DA) and Principal Component Analysis-Linear Discriminant (PCA-DA) (*Kazazić et al.*, 2021; *Paradkar et al.*, 2002a; *Gayo et al.*, 2006).

In general, linear chemometric methods from IR spectroscopic data can be evaluated with several parameters. The parameters most used, including calibration and cross-validation (CV), are the determination coefficients (R^2), the coefficients correlation (r), the Root Mean Square Error (RMSE) and the Standard Error (SE). In addition, some use difference average value between predicted and measured values (Bias), Range Error Ratio (RER), and Predicted Deviation Ratio (RPD). Each parameter has its own purpose in evaluating the model. Coefficient determination indicates how well a model performs in terms of the proportion of variance in the dependent variable predicted by the independent variables. The RPD shows the robustness of the model. SE and RMSE indicate the level of precision and accuracy of the developed model.

Non-linear approach

Another method to analyse near infrared and infrared spectroscopy data of adulteration in food and agro-products associated with chemometrics is a non-linear approach. This approach is required when the connection between the spectral absorption region of the IR spectroscopy is non-linear. The origin of these non-linear relationships is diverse and challenging to identify, but according to *Ramírez-Morales et al.* (2016), in some cases, due to the disparities in viscosity, temperature, pH, particle dimensions, and chemical content. Calibration is generally achieved utilizing non-linear methods and multivariate analysis for this reason. A reasonable variable selection aimed at collecting a small sub-group with lower sensitivity to non-linear or excluding the most wavelengths is usually effective in enhancing the model's performance (*Kaufmann et al.*, 2022; *Pandiselvam et al.*, 2022).

The research that applies a non-linear approach in chemometrics for detecting and authenticating adulteration on food and agro-product is currently in constant expansion. As mentioned before, a non-linear approach to analysing near infrared and infrared spectroscopy data can also perform qualitative analysis and quantitative prediction of adulteration in food and agro-products. Machine learning-based chemometric research is rapidly expanding at the moment. ANN, CNN, k-NN, RBFNN, RF, SVM are also more reported to analyze IR spectroscopy data of adulteration in food and agro-product as these techniques are based on pattern recognition (*Weng et al.*, 2020; *Ding and Xu*, 2000; *Le Nguyen Doan et al.*, 2021).

SOME CASE ADULTERATION ON FOOD AND AGRO-PRODUCTS

Near infrared and infrared spectroscopy analysis has been applied to both detecting and discriminating adulteration of food and agro-products. Qualitative evaluation can be the detecting of adulteration in livestock products, flour products, liquid agro-product, and herbs and spices (Table 1). In contrast, the quantitative study concentrates on predicting multiple contents adulteration of food and agro-products has been reported quite a lot recently (Table 2). In the present studies, various IR spectroscopy ranges are utilized for the quantitative and qualitative analysis of food and agro-products, including near infrared and infrared spectroscopy data (Table 3).

Table 1

Some qualitative study of food and agro-product adulteration

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of: Pre-treatment	The best of: Algorithm	Prediction results
1	(*de Araújo et al.*, 2021)	Gourmet ground roasted coffees (90)	Traditional and superior coffees	1205 – 2128	Offset correction	SIMCA	Specificity = 100%
2	(*Srinuttrakul et al.*, 2021)	Hom Mali rice (170)	Rice from northern and north-eastern regions of Thailand	740 – 1070 2500 – 22222	MSC+ 1st dev	PLS-DA	Accuracy =84.85 – 86.96% Accuracy = 96.97 –100%
3	(*Tan et al.*, 2021)	Stingless bee honey (30)	High fructose corn syrup	900 – 1700	Cutting + Gaussian smoothing	LR	Accuracy = 98.2%
4	(*dos Santos Pereira et al.*, 2021a)	Goat milk (146)	Cow milk	900 – 1650	Moving mean + Baseline offset	iSPA-PLS-DA	Accuracy = 98.3%
5	(*Shannon et al.*, 2021)	Basmati rice (1399)	Other varieties basmati rice	740 – 1070	Raw	PLS-DA	F1_score = 0.93
6	(*Tao et al.*, 2021)	Wheat flour (48)	Eight varieties of cassava flour	1150 – 2150	Raw	PLS-DA	Accuracy = 97.53%
7	(*Galvin-King et al.*, 2021b)	Garlic (117)	12 types of white powder	833 – 2500 2500 – 18182	SNV + 1st dev SG	OPLS-DA	Youden index = 0.98 Youden index = 1
8	(*Teixeira et al.*, 2021b)	Yogurt and Cheese from goat milk (576)	Cow milk	1000 – 2500	Smoothing + 2nd dev SG	PLS-DA	Sensitivity = 99.2 – 100% Specificity = 99.2 – 100%
9	(*Torres et al.*, 2021)	Sweet almonds (216)	Bitter almonds	950 – 1650	SNV + 1st dev SG	PLS-DA	Non-error rate = 86 – 100%
10	(*Le Nguyen Doan et al.*, 2021)	High-quality rice (200)	Low-quality rice	740 – 1070	1st dev SG + mean centered	PLS-DA	Accuracy = 82.6%
11	(*Cantarelli et al.*, 2020)	Cinnamon verum (120)	Cinnamon cassia	940 – 1640	Raw	PNN	Accuracy = 99.25%
12	(*Huang et al.*, 2020b)	Honey (224)	Syrup	1000 – 2500 2222 – 12500	2nd dev SG	SVMC	Accuracy = 100%

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of		Prediction results
					Pre-treatment	Algorithm	
13	(*Galvin-King et al.*, 2020b)	Powdered paprika (159)	Varying seed/pod	833 – 2500 2500 – 18182	SNV + 1st + 2nd dev SG SNV + 1st dev SG	OPLS-DA	R2 = 0.85 R2 = 0.94
14	(*Alamar et al.*, 2020)	Guava pulp (240)	Sugar and water	1000 – 2500 2500 – 25000	MSC	k-NN	Accuracy = 100% Accuracy = 100%
15	(*De Girolamo et al.*, 2020a)	Durum wheat pasta from Italy (280)	Durum wheat pasta from Argentina	1000 – 2500 2500 – 25000	Mean baseline + detrending MSC + detrending	PLS-DA	Accuracy = 97 – 100% Accuracy = 96 – 97%
16	(*Teixeira et al.*, 2020)	Goat milk (600)	Water, urea, bovine whey, and cow's milk	1000 – 2500	1st dev SG + SNV	PLS-DA	Precision = 100%
17	(*Visconti et al.*, 2020)	Grated cheese (196)	Microcrystalline cellulose, silicon dioxide, wheat-flour, wheat-semolina, sawdust	1000 – 2500	1st dev SG	PLS-DA	Precision = 100%
18	(*Jahani et al.*, 2020)	Lime juices (56)	Water and citric acid	900 – 1700	MSC	k-NN	Precision = 100%
19	(*Wilde et al.*, 2019)	Black pepper (126)	papaya seeds, chili and non-functional black pepper material	833 – 2500 2500 – 25000	SNV + 1st dev SG	OPLS-DA	Precision = 90 – 100% Precision = 92 – 100%
20	(*Karunathilaka et al.*, 2018)	Milk powder (383)	11 potential adulterants	800 – 2500	SNV + 1st dev SG	SIMCA	Accuracy = 100%
21	(*Chen et al.*, 2017)	Milks (102)	Melamine	1000 – 2500	SNV	OC-PLS	Accuracy = 89%
22	(*Shen et al.*, 2016)	Soybean meal (88)	Six types of non-protein nitrogen	1282 – 2500	1st dev SG + SNV	PLS-DA	Sensitivity = 100%
23	(*Ziegler et al.*, 2016)	Wheat kernels and flours (1225)	Bread wheat, spelt, durum, emmer, and einkorn	1200 – 2400, 650 – 2500	1st dev SG	PLS-DA	Accuracy = 80 – 100%
24	(*Xu et al.*, 2015)	Tea (100)	Exogenous amino acids	833 – 2500	SNV	PLS-DA	Accuracy = 0.936
25	(*Schmutzler et al.*, 2015)	Pork meat (84)	Pork fat	833 – 2500	2nd dev SG	SVMC	Accuracy = 83.3%
26	(*Botelho et al.*, 2015)	Raw cow milk (155)	Water, starch, sodium citrate, formaldehyde, and sucrose	2500 – 16667	1st dev SG + Smoothing	PLS-DA	Sensitivity = 88.5 – 100%
27	(*Ding et al.*, 2015)	Sweet potato powder (116)	purple and white sweet potato	700 – 2500	Selection wavelength using GA-PLS	LDA	Accuracy = 100%
28	(*López et al.*, 2014)	Hazelnut paste (135)	Almond paste and Chickpea flour	1000 – 2740	Offset correction	SIMCA	Accuracy = 96.3%
29	(*Zhang et al.*, 2014)	Raw cow milk (800)	pseudo proteins (urea, ammonium nitrate, melamine) and thickeners (dextrin and Starch)	1000 – 2500	SNV	SVMC	Precision = 96.62%
30	(*Xu et al.*, 2013a)	Chinese glutinous rice flour (215)	Extraneous adulterants, unwanted variations	1000 – 2500	2nd dev SG	OC-PLS	Specificity = 0.92
31	(*Xu et al.*, 2013b)	Chinese yogurt (257)	Edible gelatine, industrial gelatine, soy protein powder	833 – 2500	SNV	OC-PLS	Specificity = 0.95
32	(*Xu et al.*, 2013c)	Lotus root powder (85)	Four cheaper starches	833 – 2500	SNV	SIMCA	Specificity = 0.94
33	(*Chen et al.*, 2011)	Honey (144)	High fructose corn syrup	1000 – 2500	1st dev SG + smoothing + mean centering	PLS-DA	Accuracy = 96.88%
34	(*Zhu et al.*, 2010)	Honey (135)	Sweeteners materials	1000 – 2500	SNV + Smoothing SG	SVM	Accuracy = 95.1%
35	(*Xie et al.*, 2008)	Pure bayberry Juice (129)	Water	800 – 2400	SNV	RBFNN	Accuracy = 97.62
36	(*Downey et al.*, 2003)	Honey (300)	Fructose and glucose	400 – 2498	2nd dev SG	PLS-DA	Accuracy = 96%

1st dev SG = First derivatives Savitzky-Golay; 2nd dev SG = Second derivatives Savitzky-Golay; iSPA-PLS-DA = Intervals SPA – Partial least squares – algorithm discriminant analysis; k-NN = k-nearest neighbour; LDA = Linear discriminant analysis; LR = Logistic Regression; MSC = Multiplicative scatter correction; OC-PLS = One class – partial least squares; OPLS-DA = Orthogonal partial least squares – discriminant analysis; PLS-DA = Partial least squares – discriminant analysis; PNN = Probabilistic neural network; RBFNN = Radial basis function neural networks; SNV = Standard normal variate; SIMCA = Soft independent modelling of class analogy; SVMC = Support vector machines classification.

Table 2

Some quantitative study of food and agro-products adulteration

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of		Prediction results
					Pre-treatment	Algorithm	
1	(*Ndlovu et al.*, 2021a)	Green banana flour (72)	Wheat flour	400 – 2500	SNV + Baseline	PLSR	RPD = 3.9
2	(*Ndlovu et al.*, 2021b)	Green banana flour (66)	Wheat flour	400 – 2500	2^{nd} dev + Detrend	PLSR	RPD = 6.24
3	(*Ayvaz et al.*, 2021b)	Einkorn flour (64)	Wheat flour	1000 – 2500	MN + MSC + 1^{st} dev	PLSR	RPD=19.3
4	(*Santos et al.*, 2021)	Cocoa solids (110)	Cocoa solids content	1100 – 2500	SNV	PLSR	RPD = 31.09
				2500 – 16667			RPD = 17.28
5	(*Valinger et al.*, 2021b)	Acacia honey (135)	Fructose corn syrup	325 – 900; 904 – 1699	Raw	PLSR	RPD = 3.32
6	(*Wongsaipun et al.*, 2021)	Thai Jasmine Rice (423)	3 type rice	400 – 2498	Normalization	PLSR	RMSEP = 2.6; R^2p = 0.98
7	(*Castro et al.*, 2021)	Saffron (38)	Onion, Calendula, Pomegranate and Turmeric	1000 – 2500	2^{nd} dev SG + SNV	MCR-ALS	RMSEP = 0.8 – 2.3
8	(*Liu et al.*, 2021)	Infant formula (200)	Hydrolyzed leather protein and melamine	900 – 1700	1^{st} dev	CNN	R^2p=0.96 – 0.99
9	(*Aykas and Menevseoglu*, 2021)	Powdered Pistachio (19)	Powdered green pea and peanut	2500 – 15385	2^{nd} dev SG + Smoothing	PLSR	rval = 0.99
				1351 – 2551			rval = 0.99
10	(*Masithoh et al.*, 2021)	Arenga pinnata sugar (187)	Coconut sugar	1000 – 2500	MSC	PLSR	RMSEP = 12.42
				2500 – 15385	Normalization		RMSEP = 6.95
11	(*Genis et al.*, 2021)	Pistachio nut (143)	Green pea and spinach nut	908 – 1695	Raw	PLSR	RMSEP = 4.69 – 7.87
12	(*Silva et al.*, 2020)	Ground meat chicken (150)	Beef, pork	908 – 1676	1^{st} dev SG + MSC	SVMR	RMSEP = 3.5 – 4.7
13	(*Yang et al.*, 2020)	Manuka honey (93)	Five different syrups	400 – 2500	2^{nd} dev SG	PLSR	RMSEP = 3.61
				1100 – 2500			
14	(*Rukundo et al.*, 2020)	Dried turmeric powder (120)	Metanil yellow	780 – 2500	1^{st} dev SG	PLSR	RPD = 10.3
15	(*Uysal and Boyaci*, 2020)	Liquid egg (100)	Water	1000 – 2500	Baseline, autoscale, smoothing, 1st dev SG	PCR	RMSECV = 0.8 – 0.74
				2500 – 25000		PCR	RMSECV = 0.12 – 17.4
16	(*Ndlovu et al.*, 2019)	Unripe banana flour (82)	Wheat flour	447– 1005	2^{nd} dev SG	PLSR	RPD = 12.02
17	(*Kar et al.*, 2019)	Turmeric powder (200)	Corn starch	1000 – 2500	SNV + 1^{st} dev SG	PLSR	RMSEP = 0.26; R^2p = 0.99
18	(*Pereira et al.*, 2019)	Butter oil (33)	Soybean oil	833 – 2500	Raw	PLSR	RPD = 21.68
				2500 – 25000			RPD = 12.27
19	(*Yasmin et al.*, 2019)	Cinnamon Powder (195)	Lower quality cinnamon Powder	1000 – 2500	2^{nd} dev SG	PLSR	R^2p = 0.97; RMSEP = 2.2
				2857 – 15385			R^2p = 0.96; RMSEP = 2.5
20	(*Lukacs et al.*, 2018)	Whey protein powder (279)	Urea, L-taurine, L-histidine	800 – 2750	Smoothing, SNV, 2^{nd} dev SG	PLSR	R^2p > 0.98
21	(*Da Silva Dias et al.*, 2018)	Raw milk (50)	Water	1200, 1450, 1530,	Raw	MLR	R^2_p = 0.96, RMSEP = 0.018
22	(*Picouet et al.*, 2018)	Sunflower oil (138)	Mineral oil	1000 – 2200	Baseline, MSC, SNV	PLSR	RMSEP = 0.23 – 1.26
23	(*Kar et al.*, 2018)	Turmeric Powder (248)	Metanil yellow	1000 – 2500	1^{st} dev SG	PLSR	R^2p = 0.91
24	(*Correia et al.*, 2018)	Arabica coffee (125)	Robusta coffee, corn, peels, and sticks	908 – 1676	1^{st} dev SG	PLSR	RPD = 64.23

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of		Prediction results
					Pre-treatment	Algorithm	
25	(*Liu and Zhou*, 2017)	Apple juice (31)	Water	830 – 2490	MSC	SPA-PSO-PLS	R^2p = 0.99; RMSEP = 0.063
26	(*Bázár et al.*, 2016)	Honey (492)	High fructose corn syrup	1100 – 2500	Smoothing + SNV + 2^{nd} dev SG	PLSR	R^2cv = 0.987; RMSECV = 1.48
27	(*Dvorak et al.*, 2016)	Goat milk for cheeses (48)	Cow's milk	1000 – 2500	Raw	PLSR	R^2cv = 0.783
28	(*Winkler-Moser et al.*, 2015)	Coffea arabica (84)	Corn	400 – 2500	1^{st} dev SG	PLSR	R^2cv = 0.974
29	(*Kumaravelu and Gopal*, 2015)	Honey (160)	Jaggery	400 – 2500	Smoothing + SNV	PLSR	R^2_p = 0.99
	(*Mouazen and Al-Walaan*, 2014)	Honey (345)	Glucose syrup	305 – 2200	SNV + 1^{st} dev SG + Smoothing	PLSR	R^2p = 0.78, RPD = 2.06
30	(*Lohumi et al.*, 2014)	Onion powder (180)	Corn starch	1000 – 2500	SNV	PLSR	R^2p = 0.90
31				2500 – 15385			R^2p = 0.98
32	(*Vichasilp and Poungchompu*, 2014)	Beef and chicken Meatballs (140)	Pork meat	1000 – 2500	Raw	PLSR	R^2v = 0.88 – 0.83
	(*Wang et al.*, 2014)	Oat flour (220)	Wheat flour	833 – 2500	2^{nd} dev SG	PLSR	RMSEP = 1.975
33	(*Santos et al.*, 2013)	Bovine milk (744; 372 – 837)	Tap water, whey, synthetic milk, synthetic urine, urea, and hydrogen peroxide	1600 – 2400	Raw	PLSR	R^2v = 0.92
34				2500 – 15385			R^2v = 0.92 – 0.98
35	(*Öztürk et al.*, 2010)	Olive oil (160)	Soybean, cotton, corn, canola and sunflower oils	1000 – 2500	Raw	GILS	SEP = 2.93 – 5.86 rv = 0.90 – 0.99
36	(*Mishra et al.*, 2010)	Honey (56)	Jaggery syrup	1380 – 1960	Raw	PLSR	R^2v = 0.66
37	(*Pizarro et al.*, 2007)	Arabica coffee powder (191)	Robusta coffee powder	1100 – 2500	1^{st} dev SG + OWAVEC	PLSR	R^2p = 1
38	(*Özdemir and Öztürk*, 2007)	Olive oil (52)	Sunflower and corn oil	1000 – 2500	Raw	GILS	R^2p = 0.99
39	(*Gayo and Hale*, 2007)	Atlantic blue crabmeat (110)	Blue swimmer crabmeat	400 – 2498	1^{st} dev SG	PLSR	R^2p = 0.98
40	(*Cocchi et al.*, 2006)	Durum wheat flour (58)	Bread wheat flour	400 – 2498	SNV	PLSR	RMSEP = 0.38
41	(*Gayo et al.*, 2006)	Crab meat (66)	Surimi-based imitation crab meat	400 – 2498	1^{st} dev SG	PCR	R^2p = 0.99; SEP = 0.24
42	(*Jha and Matsuoka*, 2004)	Cow Milk (125)	Urea, NaOH, Oil, shampoo	700 – 1124	MSC	MLR	R^2v = 0.58 – 0.98
43	(*Uddin and Okazaki*, 2004)	Fresh (162)	Frozen-thawed fish	1920 – 2350	2^{nd} dev SG	MLR	R^2c = 0.95 – 0.99
44	(*Maraboli et al.*, 2002)	Milk powder (155)	Vegetable proteins	1100– 2500	1^{st} dev SG	MLR	R^2p = 0.993
45	(*Rodriguez-Saona et al.*, 2001)	Fruit juices (60)	Sugars	1000 – 2500	2^{nd} dev SG	PLSR	R^2p = 0.99
46	(*Wesley et al.*, 1995)	Olive oil (310)	Corn oil, sunflower oil, raw olive residue oil	800 – 2500	1^{st} dev SG	PLSR	rv = 0.8

CNN = Convolutional neural network; GILS = Genetic inverse least squares; MCR-ALS = Multivariate curve resolution – alternating least squares; MLR = Multiple linear regression; PCR = Principal component regression; PLSR = Partial least squares regression; SVMR = Support vector machines regression

Table 3

Combine qualitative and quantitative analysis of food and agro-products adulteration

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of		Prediction results
					Pre-treatment	Algorithm	
1	(*Kazazić et al.*, 2021)	Butter (36)	Pork fat, Margarine	900 – 1700	Raw	PLS-DA	Accuracy = 100%
						PLSR	RPD = 5.24 – 37.51
2	(*Amirvaresi et al.*, 2021)	Saffron (120)	C. sativus style, safflower, rubia and calendula	833 – 2500	MN + 2^{nd} dev	PLS-DA	Accuracy = 95.4 –100%
						PLSR	R^2 = 0.95 – 0.99

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of		Prediction results
					Pre-treatment	Algorithm	
				2500 – 25000		PLS-DA	Accuracy = 81.3 – 100%
3	(*Hosseini et al.*, 2021)	Sterilized milk (11)	Sodium dodecyl sulphate	769 – 2500	MN + SD scaled	PLS-DA	R^2cv = 0.98
					2^{nd} dev+SNV	PLSR	R^2p = 0.96
				2500 – 16667	Smoothing SG	PLS-DA	R^2cv = 0.94
						PLSR	R^2p = 0.98
4	(*Du et al.*, 2021a)	Camellia oil (130)	Corn oil, rapeseed oil and sunflower oil	1000 – 2381	1^{st} dev SG	DA	Accuracy = 96.7%
					SNV + 1^{st} dev SG	PLSR	RMSEP = 4.98
5	(*Le Nguyen Doan et al.*, 2021)	Green tea (475)	Sugar and glutinous rice flour	900 – 1700	SNV	SVMC	Accuracy = 97.47%
						SVMR	rp > 0.94
6	(*Vitalis et al.*, 2020)	Tomato paste (57)	Ground paprika seed, Corn starch, Sucrose, Salt	740 – 1700	1^{st} dev SG + MSC	LDA	Precision = 78.64% – 97.65%
						PLSR	RMSECV = 0.23 – 0.89
7	(*Temizkan et al.*, 2020a)	Yoghurt (100)	Several fat-free UHT	1000 – 2500	MN + MSC	SIMCA	Specificity = 100%
					MN + 1^{st} dev SG + MSC	PLSR	RPD = 4.35
				2500 – 15385	MN + 2^{nd} dev SG	SIMCA	Specificity = 100%
						PLSR	RPD = 4.65
8	(*Mabood et al.*, 2020)	Fresh milk samples (162)	Urea	1000 – 2500	Baseline	PLS-DA	R^2 = 0.97
						PLSR	R^2 = 0.98
9	(*Leng et al.*, 2020)	Minced beef (150)	Pork and Duck meat	800 – 1852	Raw	DA	Accuracy = 91.5 –100%
					Raw	PLSR	RMSEP = 7.27 – 9.27
10	(*Pereira et al.*, 2020)	Goat milk (112)	Cow milk	1000 – 2500	Raw	PLS-DA	Accuracy = 100%
					Moving mean + Baseline offset	SPA	RPD = 10
11	(*Weng et al.*, 2020)	Minced beef (240)	Beef loin, beef heart, beef tallow, and pork loin	1000 – 2500	SG smoothing	CNN	Accuracy = 99%
					CARS	RF	RMSEP = 2.145
12	(*Biancolillo et al.*, 2020)	Egg pasta (100)	Turmeric	1000 – 2500	MSC	PLS-DA	Precision = 97.5%
					SNV	PLSR	RMSEP = 0.11
13	(*Oliveira et al.*, 2020)	Paprika powder (315)	Potato starch, acacia gum and annatto	900 – 1700	Auto-scaling	PLS-DA	Specificity = 90%
					Smoothing + 1^{st} dev SG	PLSR	RMSEP = 0.95 – 1.74
14	(*Kene Ejeahalaka and On*, 2020)	Fat-filled milk powder (150)	Melamine, urea and 4 different vegetable oils	850 – 2500	2^{nd} dev SG + EMSC	SIMCA	Sensitivity = 85%
						PLSR	R^2p = 0.96
15	(*Lima et al.*, 2020)	Black pepper and Cumin (130)	Starch cassava, corn flour	1100 – 2500	Raw	O-PLS-DA	Specificity = 100%
						PLSR	RPD = 2.24 – 7.01
16	(*Aliaño-González et al.*, 2019)	Honey (68)	Inverted sugar, rice syrup, brown cane sugar and fructose syrup	400 – 2500	Raw	LDA	Precision = 100%
						PLSR	RMSEP = 3.89
17	(*Zaukuu et al.*, 2019)	Paprika powder (54)	Corn flour	750 – 1700	Smoothing + MSC	LDA	Accuracy = 95.55%
						PLSR	R^2cv = 0.98; RMSECV = 1.71
18	(*Ferreiro-González et al.*, 2018)	Honey (22)	High fructose corn syrup	400 – 2500	Raw	PCA-LDA	Accuracy = 100%
						PLSR	R^2p = 0.99, RMSEP = 4.71
19	(*Quelal-Vásconez et al.*, 2018)	Cocoa powder (234)	Carob flour	1100 – 2500	2^{nd} dev SG + OSC	PLS-DA	Accuracy = 100%
					OSC	PLSR	R^2p = 0.97, RMSEP = 3.2
20	(*Mabood et al.*, 2018)	Fruit juice (198)	Saccharin	1000 – 2500	Baseline correction + Smoothing SG	PLS-DA	R^2cv = 0.98
						PLSR	R^2p = 0.97
21	(*Rady and Adedeji*, 2018)	Minced beef (1697)	Another beef		Normalization + 1^{st} dev SG	SVMC	Precision = 100%

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of Pre-treatment	The best of Algorithm	Prediction results
				200 – 1100, 900 – 1700		PLSR	RPD = 1.64 – 1.98
22	(*Mabood et al.*, 2017b)	Camel milk (54)	Cow milk	1000 – 2500	1st dev SG	PLS-DA	R^2 = 0.97
						PLSR	R^2 = 0.92; RMSEP = 1.32
23	(*Mabood et al.*, 2017a)	Camel milk (54)	Goat milk	700 – 2500	Baseline correction + Smoothing SG	PLS-DA	R^2 = 0.97
						PLSR	R^2 = 0.94
24	(*Liu et al.*, 2017)	Honey (360)	High-fructose corn syrup, maltose syrup	1000 – 2500	Norris + 2nd dev	PLS-DA	Accuracy = 86.3% – 96.1%
					Norris + 1st dev	PLSR	R^2p = 0.9 – 0.98
25	(*Liu and Zhou*, 2017)	Infant formula (170)	Hydrolysed leather protein powder	900 – 1700	MSC + 1st dev SG	SIMCA	Accuracy = 98.21%
						SVMR	RPD = 7.42
26	(*Alamprese et al.*, 2016)	Minced beef meat (198)	Turkey meat	800 – 2667	SNV	PLSDA	Sensitivity = 0.84
						PLSR	R^2p = 0.884; RMSEP = 10.8
27	(*Capuano et al.*, 2015)	Skim milk powder (384)	Whey, starch, maltodextrin,	400 – 2498	SNV + 2nd dev SG + mean centering	SIMCA	Accuracy = 82.42%
						PLSR	R^2_p = 0.93 – 0.98
28	(*Kuswandi et al.*, 2015)	Beef meatball (162)	Pork meat	850 – 2000	1st dev SG	LDA	Accuracy = 100%
						PLSR	R^2_p = 0.97
29	(*Luqing et al.*, 2015)	Roasted green tea (150)	Sugar and glucose syrup	800 – 2500	SLB, Min/max	PLS-DA	Accuracy = 96 – 100%
					SNV	PLSR	R^2p = 0.99
30	(*Teye et al.*, 2014)	Fermented cocoa beans (132)	Unfermented cocoa beans	1000 – 2500	SNV	SVMC	Accuracy = 100%
					Selection wavelength using Si-PLS	PLSR	rp = 0.98; RMSEP = 1.68
31	(*Alamprese et al.*, 2013)	Minced beef (242)	Turkey meat	800 – 2667	SNV	LDA	Accuracy = 71.2%
						PLSR	R^2 = 98.13
32	(*Morsy and Sun*, 2013)	Minced beef (191)	Pork, fat trimming and offal	400 – 2500	2nd dev SG, SNV, Moving average	PLS-DA	Accuracy = 100%
						PLSR	R^2p = 0.82 – 0.96
33	(*Zhao et al.*, 2013)	Beefburger (164)	Offal	850 – 1098	2nd dev SG, MSC,	PLS-DA	Accuracy = 88.9 – 95.5%
					Raw	PLSR	RPD = 1.5 – 2.3
34	(*Liu et al.*, 2010)	Fishmeal (276)	Melamine	833 – 2500	2nd dev SG + Smoothing	PLS-DA	Accuracy = 99.5%
					1st dev SG + Smoothing + SNV	PLSR	R^2p = 0.98 – 0.99; RMSEP = 0.38 – 0.24
35	(*Kasemsumran et al.*, 2007)	Cow milk (90)	Water and Whey	1100 – 2500	MSC + 2nd dev SG	PLS-DA	Accuracy = 86.73 – 100%
					MSC	PLSR	R^2 = 0.99
36	(*Kelly et al.*, 2006)	Honey (179)	Beet invert syrup and High fructose corn syrup	1100 – 2498	Raw	SIMCA	Accuracy = 100%
					MSC, 2nd dev SG	PLSR	R^2 = 0.72 – 0.79
37	(*León et al.*, 2005)	Apple Juice (450)	Fructose, glucose, sucrose	400 – 2498	MSC	PLS-DA	Accuracy = 86 – 100%
						PLSR	r = 0.77 – 0.94
38	(*Downey and Kelly*, 2004)	Strawberry and raspberry purees (305)	Apples purees	400 – 2498	SNV + 2nd dev SG	SIMCA	Accuracy = 75.1–95.1%
						PLSR	rcv = 0.90
39	(*Paradkar et al.*, 2002b)	Maple syrup (272)	Cane and beet invert syrups, cane and beet sugar solutions	1100 – 1660	1st dev SG	PLS-DA	Accuracy = 98.39%
						PLSR	R^2v = 0.83 – 0.98
				2500 – 25000		PLS-DA	Accuracy = 100%
						PLSR	R^2v = 0.99
40	(*Contal et al.*, 2002)	Strawberry and raspberry purees (344)	Apples purees	400 – 2500	Raw	SIMCA	Accuracy = 79.07 – 94.77
						PLSR	rv = 0.98 – 0.99

#	Source	Objective (Sample number)	Adulterant material	Range of spectral (nm)	The best of		Prediction results
					Pre-treatment	Algorithm	
41	(*Paradkar et al.*, 2002a)	Maple syrup (54)	Corn syrups	2500 – 25000	Raw	PCA-DA	Accuracy = 96.20
						PLSR	$R^2p = 0.98$
42	(*Murray et al.*, 2001)	Fish meal (136)	Meat and bone meal	1100 – 2500	MSC	PLS-DA	Accuracy = 98.55%
					2^{nd} dv SG + SNV	PLSR	$R^2 = 0.94$
43	(*Ding and Xu*, 2000)	Beef hamburgers (194)	Mutton, pork, skim milk powder, or wheat flour	400 – 2500	SNV + 2^{nd} dev SG	k-NN	Accuracy = 92.7%
						PLSR	$R^2v = 0.74 – 1$
44	(*Thyholt et al.*, 1997)	Beef (350)	Pork, mutton	780 – 2500	1^{st} dev SG + Smoothing	QDA	Accuracy = 98.53 – 100%
						PLSR	r = 0.68 – 0.94

O-PLS-DA = Orthogonal partial least squares – discriminant analysis; PCA-LDA = Principal component analysis – linear discriminant analysis; QDA = Quadratic – discriminant analysis; RF = Random Forest; SPA = Successive projections algorithm

Adulteration in livestock products

Adulteration of livestock products occurs often and considerably threatens human health and safety when other substances are added for specific purposes. *Liu et al.* (2021) reported machine learning in the form of a CNN architecture in tandem with near infrared spectroscopy data to predict hydrolysed leather protein and melamine in infant formula. Their result can predict adulterated and unadulterated milk R^2 up to 0.99%. Furthermore, Mabood also developed a method using near infrared spectroscopy in tandem with multivariate analysis to detect the mixture of camel milk with goat milk. They used PLS-DA to authenticate pure and adulterated milk and PLS to quantify adulteration levels with RMSE of 0.08% and 1.10%, respectively. Unfortunately, the model of this study still found inconsistent accuracy at the adulteration limit of 0.5% for authentication and 2% for quantification.

Even more amazing, *Karunathilaka et al.* (2018) proposed a methodology to rapidly evaluate commercial milk powders to determine if they are original or may include known or unknown adulterants using SIMCA classification algorithm. They claim that the classification models produced 100% sensitivities using benchtop spectrometers to detect milk powder fraud and are not limited only to specific types of known adulterants. This shows that using near infrared spectroscopy with the appropriate processing method will provide very precise and fast evaluation results for fraudulent food and agro-products.

Another issue in the livestock product is meat adulteration. Unscrupulous traders adulterate meat products with another adulterant (cheaper meat, animal offal, spoiled meat, and non-meat chemical synthetic materials) for profiteering purposes. Hence, *Zhao et al.* (2019) report the VIS-NIR technique to predict beef adulteration with spoiled beef using the LS-SVM algorithm. They declare that applying LS-SVM in the spectral range of 496 to 1000 nm can predict spoiled beef with an error prediction of approximately 5.67%. Weng et al. [52] conducted another research on the detection of adulteration meat using VIS-NIR spectroscopy was conducted by *Weng et al.* (2020) with minced beef samples. They used a spectral range of 350–2500 nm and claimed to detect minced beef mixed with pork and beef heart with error predictions of approximately 2.145% and 2.758%, respectively. These studies show that the application of VIS-NIR spectroscopy coupled with chemometrics can be powerful for the fast and accurate detection of adulterated livestock products.

Adulteration in flour products

The detection of fraud in flour products ingredients has become an even more important topic since flour products, such as bread and other bakery products, are widely consumed as primary foods. Many consumers lost trust in the food they were buying and the food industry identified that more rapid measures in terms of the evaluation of its product had to be put in place. Frequently adulteration is achieved in high-value food items and those that come through complex supply chains. The flour product that comes from food is likely more highly vulnerable to adulteration due to the complexity of the characteristics, and it is widely used for products such as bread. To address this, cutting-edge methods must be easy to use, fast and inexpensive, especially for the flour industry. The most interesting method today is the application of food fingerprinting as a detection method by IR technology. At least in the last five years, durum wheat flour, banana flour, einkorn flour, wheat flour, barley flour and cassava flour were among the flour products found to be the most commonly adulterated and the researchers have studied how to detect it using IR spectroscopy technology.

In old studies, *Cocchi et al.* (2006) ever studied the use of near infrared spectroscopy to quantify the adulteration level of durum wheat flour using the PLS algorithm. The authors claim near infrared spectroscopy data can show durum wheat flour adulteration using SNV pre-treatment. In another study by *Ndlovu et al.* (2019) considered VIS-NIR spectroscopy to detect adulteration of unripe banana flour with wheat flour.

They found that the PCA model could successfully separate samples of pure and contaminated banana flour. PLSR model also could quantify the level of adulteration. Both results of this study indicate that NIR and VIS-NIR spectroscopy could monitor the quality of flour in retail markets for the purpose of product verification.

In a recent study by *Ayvaz et al.* (2021a), near infrared spectroscopy is suggested to detect adulteration of einkorn flour with wheat flour and presents a correlation coefficient of 0.94 to 0.99. The lowest correlation coefficient is found in the adulteration ratio of wheat flour less than 7% (w/w). IR spectroscopy was also used by *Aykas and Menevseoglu* (2021) to detect the mixing of powdered pistachio with powdered green pea and peanut. Infrared spectroscopy can be correctly predicted with a coefficient correlation of about 0.99.

Furthermore, Tao published a study on the detection of eight varieties of adulterants of cassava flour in wheat flour using micro-IR spectroscopy in the range of 1150–2150 nm. The classification of this study finding that the adulteration of wheat flour with cassava flour achieved 100% accuracy, yet the level adulteration of wheat flour with cassava flour (5% to 40% adulteration) only presented correct classification rates between 56.25% and 100%. The last but not least, study reported by *Xu et al.* (2013c) used near infrared spectroscopy in the 1000–2500 nm range to classify Chinese glutinous rice flour from extraneous adulterants and unwanted variations. This study found an adulteration specificity of 0.92 with one-class partial least squares algorithms.

Adulteration in liquid agro-product

Adulteration of liquid agro-products is valued in the same way as pure products, and there is a need for fast, easy, and precise analytical methods to assess their characteristics and originality. Popular liquid agro-products obtained in the form of naturally sweet and viscous products are honey, fruit juices, and vegetable oil.

According to *Tan et al.* (2021) and *Contal, L.* (2002), the chemical content of wild honey is correlated with the season, geographical region, storage method and harvesting method, which makes it very difficult to compare other types of honey. It also makes honey very susceptible to adulteration and is valued similarly to pure honey. Evaluation the feasibility of near infrared spectroscopy technology in the rapid detection and classification of adulteration of honey has been study by some researcher. *Kelly et al.* (2006) detect adulterated honey from beet invert syrup and high fructose corn syrup using near infrared spectroscopy (1100–2498 nm) with an accuracy between 9.0 and 11.9 (RMSE-CV). Furthermore, the same study was also conducted by *Bázár et al.* (2016) to detect corn syrup additives in honey using near infrared spectroscopy in the wavelength ranges 1300–1800 nm and reached an accuracy better than the previous study (RMSE-CV of 1.48). Besides, *Ferreiro-González et al.* (2018) used VIS-NIR spectroscopy (400–2500 nm) to predict honey adulteration with fructose-rich corn syrup and obtained an accuracy not yet better than *Bázár et al.* (2016) (RMSE-CV of 4.71). The most recent to conduct a similar study is *Valinger et al.* (2021a), which evaluated the feasibility of near infrared spectroscopy technology in the rapid detection of adulteration of honey with corn syrup. Unfortunately, the results indicate that the near infrared spectroscopy of adulterated honey can be modelled to detect fraud with an accuracy that is not yet better than the previous study. However, the interesting one in this study is that the adulteration of honey with water reported cannot be predicted with precision.

Fruit juice becomes a liquid food agro-product of the most common adulteration with artificial sweeteners, dilution with water, and fraud with low-quality or less-expensive fruit juice. Therefore, some researchers have developed a fast and low-cost method for inspecting fruit juice adulteration or dilution. In one study, *Mabood et al.* (2018) reported applications of near infrared spectroscopy (860–2500 nm) for classification of adulteration and non-adulteration in commercial fruit juices with precision between 0.067 to 0.169 (RMSE).

Adulteration in herbs and spices

Spices are highly valued agro-products because they are used in many in the world to flavour and preserve processed food. However, herbs and spices are extremely vulnerable to commercial gain motivated fraud including black pepper, garlic, saffron, and oregano.

Spices are high-value food components in weight units because they have desirable flavour characteristics and, therefore, are economically profitable targets for adulteration. To address this problem, Wilde and *Galvin-King et al.* (2021b) conducted a study on the feasibility of near infrared and infrared spectroscopy to detect adulteration in black pepper and garlic of adulterants. The developed model is claimed to classify black pepper from its adulteration with a percentage of correct between 92% to 100%. Investigation of garlic adulteration detection using parameter validation in the form of fit measurement has an accuracy in the range of 98.5% to 99.4%.

Meanwhile, *Amirvaresi et al.* (2021) applied infrared spectroscopy to authentication saffron adulteration with accuracy classification between 81.3 to 100%. Unfortunately, detection limitations are only in the range of 1.0–3.1% (w/w) for each adulterant. Work has also been carried out by *Galvin-King et al.* (2020a), who have utilized infrared spectroscopy to identify the presence of adulterate powdered paprika with Varying seed or pod. Their model claims to predict component adulteration on powdered paprika with a coefficient of determination of about 0.94.

FUTURE PERSPECTIVES

Current studies indicate the potential of near infrared and infrared spectroscopy approaches for detecting the adulteration of food and agro-products. Such a breakthrough would undoubtedly support the further implementation of near infrared and infrared spectroscopy-based quality evaluation. The availability of multiple data sources and the fusion of multi-origin data affords a perspective for future research. The fusion of UV-VIS, near infrared, and infrared spectroscopy is the process of combining some spectral information to improve data quality and produce a high quality representation model (*Valinger et al.*, 2021a). Future studies may use sample adulteration from a different origin, variety, storage temperature, or even shelf-life when developing a model. With the increasing number and high quality of accessible samples, the future perspective for detecting the adulteration of food and agro-products possibly focuses on near infrared and infrared spectroscopy tandem with machine learning. The main advantage of the machine learning approach is decreasing the dependence on human domain knowledge by end-to-end analysis and the improved precision and generalizability.

CONCLUSIONS

In this paper, the feasibility of applying a non-destructive for detecting and discriminating food adulteration and agro-products is based on near infrared and infrared spectroscopy and various types of data analysis have been represented. Besides the non-destructive, the primary advantages of the analytical method are fast and economical, directing to cost-effective quality assurance of detecting such a key worldwide food and agro-products adulteration. Actually, once the chemometric model has been correctly calibrated, the time elapsed from the scanning of IR spectroscopy on the samples and their subsequent classification would only need a few seconds. Therefore, this approach could represent a concrete and effective answer to the need, claimed by industrial and agro-product producers, as well as by the Food Control Authority, for affordable, fast, and efficient technologies to evaluate food quality and authenticity. Furthermore, the results of the variable selection establish the basis for developing portable and handheld infrared spectroscopy, customized for the detection and discrimination of adulteration food and agro-products directly “in situ” to ensure authenticity and counteract adulteration. Last but not least, the promising results performed by the numerous laboratory model validation indicate the potential transferability of a near infrared and infrared spectroscopy-based method to various production food and agro-product sites.

In the future, although optimistic results were acquired in an investigation for fraud detection for food and agro-products today, it must be pointed out that the optical for near-infrared and infrared spectroscopy technologies applied remain pricey so far. To implement routine analyses in some food and agro-products, it is necessary to develop low-cost infrared optical technologies and have the same accuracy as those currently available.

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REFERENCES

[1] Alamar, P. D., Caramês E. T. S., Poppi R. J., Pallone J. A. L. (2020). Detection of Fruit Pulp Adulteration Using Multivariate Analysis: Comparison of NIR, MIR and Data Fusion Performance. *Food Analytical Methods*, 13(6). 1357-1365.

[2] Alamprese, C., Amigo J. M., Casiraghi E., Engelsen S. B. (2016). Identification and quantification of turkey meat adulteration in fresh, frozen-thawed and cooked minced beef by FT-NIR spectroscopy and chemometrics. *Meat Science*, 121. 175-181.

[3] Alamprese, C., Casale M., Sinelli N., Lanteri S., Casiraghi E. (2013). Detection of minced beef adulteration with turkey meat by UV–vis, NIR and MIR spectroscopy. *LWT - Food Science and Technology*, 53(1). 225-232.

[4] Aliaño-González, M. J., Ferreiro-González M., Espada-Bellido E., Palma M., Barbero G. F. (2019). A screening method based on Visible-NIR spectroscopy for the identification and quantification of different adulterants in high-quality honey. *Talanta*, 203. 235-241.

[5] Amirvaresi, A., Nikounezhad N., Amirahmadi M., Daraei B., Parastar H. (2021). Comparison of near-infrared (NIR) and mid-infrared (MIR) spectroscopy based on chemometrics for saffron authentication and adulteration detection. *Food Chemistry*, 344.

[6] Aykas, D. P., Menevseoglu A. (2021). A rapid method to detect green pea and peanut adulteration in pistachio by using portable FT-MIR and FT-NIR spectroscopy combined with chemometrics. *Food Control*, 121.

[7] Ayvaz, H., Korkmaz F., Polat H., Ayvaz Z., Barış Tuncel N. (2021a). Detection of einkorn flour adulteration in flour and bread samples using Computer-Based Image Analysis and Near-Infrared Spectroscopy. *Food Control*, 127. 108162.

[8] Ayvaz, H., Korkmaz F., Polat H., Ayvaz Z., Barış Tuncel N. (2021b). Detection of einkorn flour adulteration in flour and bread samples using Computer-Based Image Analysis and Near-Infrared Spectroscopy. *Food Control*, 127.

[9] Bázár, G., Romvári R., Szabó A., Somogyi T., Éles V., Tsenkova R. (2016). NIR detection of honey adulteration reveals differences in water spectral pattern. *Food Chemistry*, 194. 873-880.

[10] Biancolillo, A., Santoro A., Firmani P., Marini F. (2020). Identification and Quantification of Turmeric Adulteration in Egg-Pasta by Near Infrared Spectroscopy and Chemometrics. *Applied Sciences*, 10(8). 2647.

[11] Botelho, B. G., Reis N., Oliveira L. S., Sena M. M. (2015). Development and analytical validation of a screening method for simultaneous detection of five adulterants in raw milk using mid-infrared spectroscopy and PLS-DA. *Food Chemistry*, 181. 31-37.

[12] Cantarelli, M. Á., Moldes C. A., Marchevsky E. J., Azcarate S. M., Camiña J. M. (2020). Low-cost analytic method for the identification of Cinnamon adulteration. *Microchemical Journal*, 159.

[13] Capuano, E., Boerrigter-Eenling R., Koot A., van Ruth S. M. (2015). Targeted and Untargeted Detection of Skim Milk Powder Adulteration by Near-Infrared Spectroscopy. *Food Analytical Methods*, 8(8). 2125-2134.

[14] Castro, R. C., Ribeiro D. S. M., Santos J. L. M., Páscoa R. N. M. J. (2021). Near infrared spectroscopy coupled to MCR-ALS for the identification and quantification of saffron adulterants: Application to complex mixtures. *Food Control*, 123.

[15] Chen, H., Tan C., Lin Z., Wu T. (2017). Detection of melamine adulteration in milk by near-infrared spectroscopy and one-class partial least squares. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 173. 832-836.

[16] Chen, L., Xue X., Ye Z., Zhou J., Chen F., Zhao J. (2011). Determination of Chinese honey adulterated with high fructose corn syrup by near infrared spectroscopy. *Food Chemistry*, 128(4). 1110-1114.

[17] Cocchi, M., Durante C., Foca G., Marchetti A., Tassi L., Ulrici A. (2006). Durum wheat adulteration detection by NIR spectroscopy multivariate calibration. *Talanta*, 68(5). 1505-1511.

[18] Contal, L., León V., Downey G. (2002). Detection and quantification of apple adulteration in strawberry and raspberry purées using visible and near infrared spectroscopy. *Journal of Near Infrared Spectroscopy*, 10(4). 289-299.

[19] Correia, R. M., Tosato F., Domingos E., Rodrigues R. R. T., Aquino L. F. M., Filgueiras P. R., Lacerda V., Romão W. (2018). Portable near infrared spectroscopy applied to quality control of Brazilian coffee. *Talanta*, 176. 59-68.

[20] Da Silva Dias, L., Da Silva J. C., De Souza Maudeira Felicio A. L., De Franca J. A. (2018). A NIR Photometer Prototype with Integrating Sphere for the Detection of Added Water in Raw Milk. *IEEE Transactions on Instrumentation and Measurement*, 67(12). 2812-2819.

[21] de Araújo, T. K. L., Nóbrega R. O., Fernandes D. D. D. S., de Araújo M. C. U., Diniz P. H. G. D., da Silva E. C. (2021). Non-destructive authentication of Gourmet ground roasted coffees using NIR spectroscopy and digital images. *Food Chemistry*, 364.

[22] De Girolamo, A., Arroyo M. C., Cervellieri S., Cortese M., Pascale M., Logrieco A. F., Lippolis V. (2020a). Detection of durum wheat pasta adulteration with common wheat by infrared spectroscopy and chemometrics: A case study. *LWT*, 127.

[23] De Girolamo, A., Arroyo M. C., Lippolis V., Cervellieri S., Cortese M., Pascale M., Logrieco A. F., von Holst C. (2020b). A simple design for the validation of a FT-NIR screening method: Application to the detection of durum wheat pasta adulteration. *Food Chemistry*, 333.

[24] Ding, H. B., Xu R. J. (2000). Near-infrared spectroscopic technique for detection of beef hamburger adulteration. *Journal of Agricultural and Food Chemistry*, 48(6). 2193-2198.

[25] Ding, X., Ni Y., Kokot S. (2015). NIR spectroscopy and chemometrics for the discrimination of pure, powdered, purple sweet potatoes and their samples adulterated with the white sweet potato flour. *Chemometrics and Intelligent Laboratory Systems*, 144. 17-23.

[26] dos Santos Pereira, E. V., de Sousa Fernandes D. D., de Araújo M. C. U., Diniz P. H. G. D., Maciel M. I. S. (2021a). In-situ authentication of goat milk in terms of its adulteration with cow milk using a low-cost portable NIR spectrophotometer. *Microchemical Journal*, 163.

[27] dos Santos Pereira, E. V., de Sousa Fernandes D. D., de Araújo M. C. U., Diniz P. H. G. D., Maciel M. I. S. (2021b). In-situ authentication of goat milk in terms of its adulteration with cow milk using a low-cost portable NIR spectrophotometer. *Microchemical Journal*, 163. 105885.

[28] Downey, G., Fouratier V., Kelly J. D. (2003). Detection of honey adulteration by addition of fructose and glucose using near infrared transflectance spectroscopy. *Journal of Near Infrared Spectroscopy*, 11(6). 447-456.

[29] Downey, G., Kelly J. D. (2004). Detection and Quantification of Apple Adulteration in Diluted and Sulfited Strawberry and Raspberry Purées Using Visible and Near-Infrared Spectroscopy. *Journal of Agricultural and Food Chemistry*, 52(2). 204-209.

[30] Du, Q., Zhu M., Shi T., Luo X., Gan B., Tang L., Chen Y. (2021a). Adulteration detection of corn oil, rapeseed oil and sunflower oil in camellia oil by in situ diffuse reflectance near-infrared spectroscopy and chemometrics. *Food Control*, 121. 107577.

[31] Du, Q., Zhu M., Shi T., Luo X., Gan B., Tang L., Chen Y. (2021b). Adulteration detection of corn oil, rapeseed oil and sunflower oil in camellia oil by in situ diffuse reflectance near-infrared spectroscopy and chemometrics. *Food Control*, 121.

[32] Dvorak, L., Mlcek J., Sustova K. (2016). Comparison of FT-NIR spectroscopy and ELISA for detection of adulteration of goat cheeses with cow's milk. *Journal of AOAC International*, 99(1). 180-186.

[33] Ferreiro-González, M., Espada-Bellido E., Guillén-Cueto L., Palma M., Barroso C. G., Barbero G. F. (2018). Rapid quantification of honey adulteration by visible-near infrared spectroscopy combined with chemometrics. *Talanta*, 188. 288-292.

[34] Galvin-King, P., Haughey S. A., Elliott C. T. (2020a). The Detection of Substitution Adulteration of Paprika with Spent Paprika by the Application of Molecular Spectroscopy Tools. *Foods*, 9(7).

[35] Galvin-King, P., Haughey S. A., Elliott C. T. (2020b). The Detection of Substitution Adulteration of Paprika with Spent Paprika by the Application of Molecular Spectroscopy Tools. *Foods*, 9(7). 944.

[36] Galvin-King, P., Haughey S. A., Elliott C. T. (2021a). Garlic adulteration detection using NIR and FTIR spectroscopy and chemometrics. *Journal of Food Composition and Analysis*, 96.

[37] Galvin-King, P., Haughey S. A., Elliott C. T. (2021b). Garlic adulteration detection using NIR and FTIR spectroscopy and chemometrics. *Journal of Food Composition and Analysis*, 96. 103757.

[38] Gayo, J., Hale S. A. (2007). Detection and quantification of species authenticity and adulteration in crabmeat using visible and near-infrared spectroscopy. *Journal of Agricultural and Food Chemistry*, 55(3). 585-592.

[39] Gayo, J., Hale S. A., Blanchard S. M. (2006). Quantitative analysis and detection of adulteration in crab meat using visible and near-infrared spectroscopy. *Journal of Agricultural and Food Chemistry*, 54(4). 1130-1136.

[40] Genis, H. E., Durna S., Boyaci I. H. (2021). Determination of green pea and spinach adulteration in pistachio nuts using NIR spectroscopy. *LWT*, 136. 110008.

[41] Hosseini, E., Ghasemi J. B., Daraei B., Asadi G., Adib N. (2021). Application of genetic algorithm and multivariate methods for the detection and measurement of milk-surfactant adulteration by attenuated total reflection and near-infrared spectroscopy. *Journal of the Science of Food and Agriculture*, 101(7). 2696-2703.

[42] Huang, F., Song H., Guo L., Guang P., Yang X., Li L., Zhao H., Yang M. (2020a). Detection of adulteration in Chinese honey using NIR and ATR-FTIR spectral data fusion. *Spectrochimica Acta - Part A: Molecular and Biomolecular Spectroscopy*, 235.

[43] Huang, F., Song H., Guo L., Guang P., Yang X., Li L., Zhao H., Yang M. (2020b). Detection of adulteration in Chinese honey using NIR and ATR-FTIR spectral data fusion. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 235. 118297.

[44] Jahani, R., Yazdanpanah H., van Ruth S. M., Kobarfard F., Alewijn M., Mahboubi A., Faizi M., Aliabadi M. H. S., Salamzadeh J. (2020). Novel application of near-infrared spectroscopy and chemometrics approach for detection of lime juice adulteration. *Iranian Journal of Pharmaceutical Research*, 19(2). 34-44.

[45] Jha, S. N., Matsuoka T. (2004). Detection of adulterants in milk using near infrared spectroscopy. *Journal of Food Science and Technology*, 41(3). 313-316.

[46] Kar, S., Tudu B., Bag A. K., Bandyopadhyay R. (2018). Application of Near-Infrared Spectroscopy for the Detection of Metanil Yellow in Turmeric Powder. *Food Analytical Methods*, 11(5). 1291-1302.

[47] Kar, S., Tudu B., Jana A., Bandyopadhyay R. (2019). FT-NIR spectroscopy coupled with multivariate analysis for detection of starch adulteration in turmeric powder. *Food Additives and Contaminants - Part A Chemistry, Analysis, Control, Exposure and Risk Assessment*, 36(6). 863-875.

[48] Karunathilaka, S. R., Yakes B. J., He K., Chung J. K., Mossoba M. (2018). Non-targeted NIR spectroscopy and SIMCA classification for commercial milk powder authentication: A study using eleven potential adulterants. *Heliyon*, 4(9). 1-23.

[49] Kasemsumran, S., Thanapase W., Kiatsoonthon A. (2007). Feasibility of near-infrared spectroscopy to detect and to quantify adulterants in cow milk. *Analytical Sciences*, 23(7). 907-910.

[50] Kaufmann, K. C., Sampaio K. A., García-Martín J. F., Barbin D. F. (2022). Identification of coriander oil adulteration using a portable NIR spectrometer. *Food Control*, 132. 108536.

[51] Kazazić, S., Gajdoš-Kljusurić J., Radeljević B., Plavljanić D., Špoljarić J., Ljubić T., Bilić B., Mikulec N. (2021). Comparison of GC and NIR spectra as a rapid tool for food fraud detection: Case of butter adulteration with different fat types. *Journal of Food Processing and Preservation*, 45(9).

[52] Kelly, J. D., Petisco C., Downey G. (2006). Potential of near infrared transflectance spectroscopy to detect adulteration of Irish honey by beet invert syrup and high fructose corn syrup. *Journal of Near Infrared Spectroscopy*, 14(2). 139-146.

[53] Kene Ejeahalaka, K., On S. L. W. (2020). Effective detection and quantification of chemical adulterants in model fat-filled milk powders using NIRS and hierarchical modelling strategies. *Food Chemistry*, 309. 125785.

[54] Kumaravelu, C., Gopal A. (2015). Detection and Quantification of Adulteration in Honey through Near Infrared Spectroscopy. *International Journal of Food Properties*, 18(9). 1930-1935.

[55] Kuswandi, B., Cendekiawan K. A., Kristiningrum N., Ahmad M. (2015). Pork adulteration in commercial meatballs determined by chemometric analysis of NIR Spectra. *Journal of Food Measurement and Characterization*, 9(3). 313-323.

[56] Le Nguyen Doan, D., Nguyen Q. C., Marini F., Biancolillo A. (2021). Authentication of rice (Oryza sativa l.) using near infrared spectroscopy combined with different chemometric classification strategies. *Applied Sciences (Switzerland)*, 11(1). 1-11.

[57] Leng, T., Li F., Xiong L., Xiong Q., Zhu M., Chen Y. (2020). Quantitative detection of binary and ternary adulteration of minced beef meat with pork and duck meat by NIR combined with chemometrics. *Food Control*, 113.

[58] León, L., Daniel Kelly J., Downey G. (2005). Detection of apple juice adulteration using near-infrared transflectance spectroscopy. *Applied Spectroscopy*, 59(5). 593-599.

[59] Lima, A. B. S. d., Batista A. S., Jesus J. C. d., Silva J. d. J., Araújo A. C. M. d., Santos L. S. (2020). Fast quantitative detection of black pepper and cumin adulterations by near-infrared spectroscopy and multivariate modeling. *Food Control*, 107. 106802.

[60] Liu, X., Jia G., Wu C., Wang K., Wu X. (2010). Determination of characteristic wave bands and detection of melamine in fishmeal by Fourier transform near infrared spectroscopy. *Journal of Near Infrared Spectroscopy*, 18(2). 113-120.

[61] Liu, Y., Zhou S. (2017). Rapid detection of hydrolyzed leather protein adulteration in infant formula by near-infrared spectroscopy. *Food Science and Technology Research*, 23(3). 469-474.

[62] Liu, Y., Zhou S., Han W., Li C., Huang K., Liu W. (2017). Detection of adulteration by hydrolysed leather protein in infant formula based on least squares support vector machine and near-infrared spectroscopy. *Journal of Food and Nutrition Research*, 56(3). 283-291.

[63] Liu, Y., Zhou S., Han W., Li C., Liu W., Qiu Z., Chen H. (2021). Detection of adulteration in infant formula based on ensemble convolutional neural network and near-infrared spectroscopy. *Foods*, 10(4).

[64] Lohumi, S., Lee S., Lee W. H., Kim M. S., Mo C., Bae H., Cho B. K. (2014). Detection of starch adulteration in onion powder by FT-NIR and FT-IR spectroscopy. *Journal of Agricultural and Food Chemistry*, 62(38). 9246-9251.

[65] López, M. I., Trullols E., Callao M. P., Ruisánchez I. (2014). Multivariate screening in food adulteration: Untargeted versus targeted modelling. *Food Chemistry*, 147. 177-181.

[66] Lukacs, M., Bazar G., Pollner B., Henn R., Kirchler C. G., Huck C. W., Kovacs Z. (2018). Near infrared spectroscopy as an alternative quick method for simultaneous detection of multiple adulterants in whey protein-based sports supplement. *Food Control*, 94. 331-340.

[67] Luqing, L., Lingdong W., Jingming N., Zhengzhu Z. (2015). Detection and Quantification of Sugar and Glucose Syrup in Roasted Green Tea Using near Infrared Spectroscopy. *Journal of Near Infrared Spectroscopy*, 23(5). 317-325.

[68] Mabood, F., Ali L., Boque R., Abbas G., Jabeen F., Haq Q. M. I., Hussain J., Hamaed A. M., Naureen Z., Al-Nabhani M., Khan M. Z., Khan A., Al-Harrasi A. (2020). Robust Fourier transformed infrared spectroscopy coupled with multivariate methods for detection and quantification of urea adulteration in fresh milk samples. *Food Science and Nutrition*, 8(10). 5249-5258.

[69] Mabood, F., Hussain J., Jabeen F., Abbas G., Allaham B., Albroumi M., Alghawi S., Alameri S., Gilani S. A., Al-Harrasi A., Haq Q. M. I., Farooq S. (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.

[70] Mabood, F., Jabeen F., Ahmed M., Hussain J., Al Mashaykhi S. A. A., Al Rubaiey Z. M. A., Farooq S., Boqué R., Ali L., Hussain Z., Al-Harrasi A., Khan A. L., Naureen Z., Idrees M., Manzoor S. (2017a). Development of new NIR-spectroscopy method combined with multivariate analysis for detection of adulteration in camel milk with goat milk. *Food Chemistry*, 221. 746-750.

[71] Mabood, F., Jabeen F., Hussain J., Al-Harrasi A., Hamaed A., Al Mashaykhi S. A. A., Al Rubaiey Z. M. A., Manzoor S., Khan A., Haq Q. M. I., Gilani S. A., Khan A. (2017b). FT-NIRS coupled with chemometric methods as a rapid alternative tool for the detection & quantification of cow milk adulteration in camel milk samples. *Vibrational Spectroscopy*, 92. 245-250.

[72] Maraboli, A., Cattaneo T. M. P., Giangiacomo R. (2002). Detection of vegetable proteins from soy, pea and wheat isolates in milk powder by near infrared spectroscopy. *Journal of Near Infrared Spectroscopy*, 10(1). 63-69.

[73] Masithoh, R. E., Roosmayanti F., Rismiwandira K., Pahlawan M. F. R. (2021). Detection of Palm Sugar Adulteration by Fourier Transform Near-Infrared (FT-NIR) and Fourier Transform Infrared (FT-IR) Spectroscopy. *Sugar Tech*.

[74] Mishra, S., Kamboj U., Kaur H., Kapur P. (2010). Detection of jaggery syrup in honey using near-infrared spectroscopy. *International Journal of Food Sciences and Nutrition*, 61(3). 306-315.

[75] Morsy, N., Sun D.-W. (2013). Robust linear and non-linear models of NIR spectroscopy for detection and quantification of adulterants in fresh and frozen-thawed minced beef. *Meat Science*, 93(2). 292-302.

[76] Mouazen, A. M., Al-Walaan N. (2014). Glucose adulteration in saudi honey with visible and near infrared spectroscopy. *International Journal of Food Properties*, 17(10). 2263-2274.

[77] Murray, I., Aucott L. S., Pike I. H. (2001). Use of discriminant analysis on visible and near infrared reflectance spectra to detect adulteration of fishmeal with meat and bone meal. *Journal of Near Infrared Spectroscopy*, 9(4). 297-311.

[78] Ndlovu, P. F., Magwaza L. S., Tesfay S. Z., Mphahlele R. R. (2019). Rapid visible–near infrared (Vis–NIR) spectroscopic detection and quantification of unripe banana flour adulteration with wheat flour. *Journal of Food Science and Technology*, 56(12). 5484-5491.
[79] Ndlovu, P. F., Magwaza L. S., Tesfay S. Z., Mphahlele R. R. (2021a). Rapid spectroscopic method for quantifying gluten concentration as a potential biomarker to test adulteration of green banana flour. *Spectrochimica Acta - Part A: Molecular and Biomolecular Spectroscopy*, 262.
[80] ——— (2021b). Vis-NIR spectroscopic and chemometric models for detecting contamination of premium green banana flour with wheat by quantifying resistant starch content. *Journal of Food Composition and Analysis*, 102.
[81] Oliveira, M. M., Cruz-Tirado J. P., Roque J. V., Teófilo R. F., Barbin D. F. (2020). Portable near-infrared spectroscopy for rapid authentication of adulterated paprika powder. *Journal of Food Composition and Analysis*, 87. 103403.
[82] Ozaki, Y., Huck C., Tsuchikawa S., Engelsen S. B., (2021). Near-Infrared Spectroscopy: Theory, Spectral Analysis, Instrumentation, and Applications (Springer)
[83] Özdemir, D., Öztürk B. (2007). Near infrared spectroscopic determination of olive oil adulteration with sunflower and corn oil. *Journal of Food and Drug Analysis*, 15(1). 40-47.
[84] Öztürk, B., Yalçin A., Özdemir D. (2010). Determination of olive oil adulteration with vegetable oils by near infrared spectroscopy coupled with multivariate calibration. *Journal of Near Infrared Spectroscopy*, 18(3). 191-201.
[85] Pandiselvam, R., Mahanti N. K., Manikantan M. R., Kothakota A., Chakraborty S. K., Ramesh S. V., Beegum P. P. S. (2022). Rapid detection of adulteration in desiccated coconut powder: vis-NIR spectroscopy and chemometric approach. *Food Control*, 133(Part A). 108588.
[86] Paradkar, M. M., Sakhamuri S., Irudayaraj J. (2002a). Comparison of FTIR, FT-Raman, and NIR spectroscopy in a maple syrup adulteration study. *Journal of Food Science*, 67(6). 2009-2015.
[87] Paradkar, M. M., Sivakesava S., Irudayaraj J. (2002b). Discrimination and classification of adulterants in maple syrup with the use of infrared spectroscopic techniques. *Journal of the Science of Food and Agriculture*, 82(5). 497-504.
[88] Pereira, C. G., Leite A. I. N., Andrade J., Bell M. J. V., Anjos V. (2019). Evaluation of butter oil adulteration with soybean oil by FT-MIR and FT-NIR spectroscopies and multivariate analyses. *LWT*, 107. 1-8.
[89] Pereira, E. V. D. S., Fernandes D. D. D. S., de Araújo M. C. U., Diniz P. H. G. D., Maciel M. I. S. (2020). Simultaneous determination of goat milk adulteration with cow milk and their fat and protein contents using NIR spectroscopy and PLS algorithms. *LWT*, 127.
[90] Picouet, P. A., Gou P., Hyypiö R., Castellari M. (2018). Implementation of NIR technology for at-line rapid detection of sunflower oil adulterated with mineral oil. *Journal of Food Engineering*, 230. 18-27.
[91] Pizarro, C., Esteban-Díez I., González-Sáiz J. M. (2007). Mixture resolution according to the percentage of robusta variety in order to detect adulteration in roasted coffee by near infrared spectroscopy. *Analytica Chimica Acta*, 585(2). 266-276.
[92] Quelal-Vásconez, M. A., Pérez-Esteve É., Arnau-Bonachera A., Barat J. M., Talens P. (2018). Rapid fraud detection of cocoa powder with carob flour using near infrared spectroscopy. *Food Control*, 92. 183-189.
[93] Rady, A., Adedeji A. (2018). Assessing different processed meats for adulterants using visible-near-infrared spectroscopy. *Meat Science*, 136. 59-67.
[94] Ramírez-Morales, I., Rivero D., Fernández-Blanco E., Pazos A. (2016). Optimization of NIR calibration models for multiple processes in the sugar industry. *Chemometrics and Intelligent Laboratory Systems*, 159. 45-57.
[95] Reich, G. (2016). 'Mid and near infrared spectroscopy.' in, *Analytical Techniques in the Pharmaceutical Sciences* (Springer)
[96] Rodriguez-Saona, L. E., Fry F. S., McLaughlin M. A., Calvey E. M. (2001). Rapid analysis of sugars in fruit juices by FT-NIR spectroscopy. *Carbohydrate Research*, 336(1). 63-74.
[97] Rukundo, I. R., Danao M.-G. C., Weller C. L., Wehling R. L., Eskridge K. M. (2020). Use of a handheld near infrared spectrometer and partial least squares regression to quantify metanil yellow adulteration in turmeric powder. *Journal of Near Infrared Spectroscopy*, 28(2). 81-92.

[98] Rukundo, I. R., Danao M. C. (2020). Identifying turmeric powder by source and metanil yellow adulteration levels using near-infrared spectra and PCA-SIMCA modeling. *Journal of Food Protection*, 83(6). 968-974.
[99] Santos, I. A., Conceição D. G., Viana M. B., Silva G. D. J., Santos L. S., Ferrão S. P. B. (2021). NIR and MIR spectroscopy for quick detection of the adulteration of cocoa content in chocolates. *Food Chemistry*, 349.
[100] Santos, P. M., Pereira-Filho E. R., Rodriguez-Saona L. E. (2013). Application of hand-held and portable infrared spectrometers in bovine milk analysis. *Journal of Agricultural and Food Chemistry*, 61(6). 1205-1211.
[101] Schmutzler, M., Beganovic A., Böhler G., Huck C. W. (2015). Methods for detection of pork adulteration in veal product based on FT-NIR spectroscopy for laboratory, industrial and on-site analysis. *Food Control*, 57. 258-267.
[102] Shannon, M., Ratnasekhar C. H., McGrath T. F., Kapil A. P., Elliott C. T. (2021). A two-tiered system of analysis to tackle rice fraud: The Indian Basmati study. *Talanta*, 225.
[103] Shen, G., Fan X., Yang Z., Han L. (2016). A feasibility study of non-targeted adulterant screening based on NIRM spectral library of soybean meal to guarantee quality: The example of non-protein nitrogen. *Food Chemistry*, 210. 35-42.
[104] Silva, L. C. R., Folli G. S., Santos L. P., Barros I. H. A. S., Oliveira B. G., Borghi F. T., Santos F. D. D., Filgueiras P. R., Romão W. (2020). Quantification of beef, pork, and chicken in ground meat using a portable NIR spectrometer. *Vibrational Spectroscopy*, 111.
[105] Srinuttrakul, W., Mihailova A., Islam M. D., Liebisch B., Maxwell F., Kelly S. D., Cannavan A. (2021). Geographical differentiation of hom mali rice cultivated in different regions of thailand using ftir-atr and nir spectroscopy. *Foods*, 10(8).
[106] Tan, S. H., Pui L. P., Solihin M. I., Keat K. S., Lim W. H., Ang C. K. (2021). Physicochemical analysis and adulteration detection in Malaysia stingless bee honey using a handheld near-infrared spectrometer. *Journal of Food Processing and Preservation*, 45(7).
[107] Tao, F., Liu L., Kucha C., Ngadi M. (2021). Rapid and non-destructive detection of cassava flour adulterants in wheat flour using a handheld MicroNIR spectrometer. *Biosystems Engineering*, 203. 34-43.
[108] Teixeira, J. L. D. P., Caramês E. T. D. S., Baptista D. P., Gigante M. L., Pallone J. A. L. (2020). Vibrational spectroscopy and chemometrics tools for authenticity and improvement the safety control in goat milk. *Food Control*, 112.
[109] ——— (2021a). Rapid adulteration detection of yogurt and cheese made from goat milk by vibrational spectroscopy and chemometric tools. *Journal of Food Composition and Analysis*, 96.
[110] Teixeira, J. L. d. P., Caramês E. T. d. S., Baptista D. P., Gigante M. L., Pallone J. A. L. (2021b). Rapid adulteration detection of yogurt and cheese made from goat milk by vibrational spectroscopy and chemometric tools. *Journal of Food Composition and Analysis*, 96. 103712.
[111] Temizkan, R., Can A., Dogan M. A., Mortas M., Ayvaz H. (2020a). Rapid detection of milk fat adulteration in yoghurts using near and mid-infrared spectroscopy. *International Dairy Journal*, 110. 104795.
[112] Temizkan, R., Can A., Dogan M. A., Mortas M., Ayvaz H. (2020b). Rapid detection of milk fat adulteration in yoghurts using near and mid-infrared spectroscopy. *International Dairy Journal*, 110.
[113] Teye, E., Huang X.-y., Lei W., Dai H. (2014). Feasibility study on the use of Fourier transform near-infrared spectroscopy together with chemometrics to discriminate and quantify adulteration in cocoa beans. *Food Research International*, 55. 288-293.
[114] Thyholt, K., Indahl U. G., Hildrum K. I., Ellekjær M. R., Isaksson T. (1997). Meat speciation by near infrared reflectance spectroscopy on dry extract. *Journal of Near Infrared Spectroscopy*, 5(4). 195-208.
[115] Torres, I., Sánchez M. T., Vega-Castellote M., Pérez-Marín D. (2021). Fraud detection in batches of sweet almonds by portable near-infrared spectral devices. *Foods*, 10(6).
[116] Uddin, M., Okazaki E. (2004). Classification of fresh and frozen-thawed fish by near-infrared spectroscopy. *Journal of Food Science*, 69(8). C665-C668.
[117] Uysal, R. S., Boyaci I. H. (2020). Authentication of liquid egg composition using ATR-FTIR and NIR spectroscopy in combination with PCA. *Journal of the Science of Food and Agriculture*, 100(2). 855-862.

[118] Valinger, D., Longin L., Grbeš F., Benković M., Jurina T., Gajdoš Kljusurić J., Jurinjak Tušek A. (2021a). Detection of honey adulteration – The potential of UV-VIS and NIR spectroscopy coupled with multivariate analysis. *LWT*, 145. 111316.
[119] Valinger, D., Longin L., Grbeš F., Benković M., Jurina T., Gajdoš Kljusurić J., Jurinjak Tušek A. (2021b). Detection of honey adulteration – The potential of UV-VIS and NIR spectroscopy coupled with multivariate analysis. *LWT*, 145.
[120] Vichasilp, C., Poungchompu O. (2014). Feasibility of detecting pork adulteration in halal meatballs using near infrared spectroscopy (NIR). *Chiang Mai University Journal of Natural Sciences*, 13(1). 497-507.
[121] Visconti, L. G., Rodríguez M. S., Di Anibal C. V. (2020). Determination of grated hard cheeses adulteration by near infrared spectroscopy (NIR) and multivariate analysis. *International Dairy Journal*, 104. 104647.
[122] Vitalis, F., Zaukuu J. L. Z., Bodor Z., Aouadi B., Hitka G., Kaszab T., Zsom-Muha V., Gillay Z., Kovacs Z. (2020). Detection and quantification of tomato paste adulteration using conventional and rapid analytical methods. *Sensors (Switzerland)*, 20(21). 1-21.
[123] Wang, N., Zhang X., Yu Z., Li G., Zhou B. (2014). Quantitative analysis of adulterations in oat flour by FT-NIR spectroscopy, incomplete unbalanced randomized block design, and partial least squares. *Journal of Analytical Methods in Chemistry*, 2014.
[124] Weng, S., Guo B., Tang P., Yin X., Pan F., Zhao J., Huang L., Zhang D. (2020). Rapid detection of adulteration of minced beef using Vis/NIR reflectance spectroscopy with multivariate methods. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 230. 1-9.
[125] Wesley, I. J., Barnes R. J., McGill A. E. J. (1995). Measurement of adulteration of olive oils by near-infrared spectroscopy. *Journal of the American Oil Chemists' Society*, 72(3). 289-292.
[126] Wilde, A. S., Haughey S. A., Galvin-King P., Elliott C. T. (2019). The feasibility of applying NIR and FT-IR fingerprinting to detect adulteration in black pepper. *Food Control*, 100. 1-7.
[127] Winkler-Moser, J. K., Singh M., Rennick K. A., Bakota E. L., Jham G., Liu S. X., Vaughn S. F. (2015). Detection of Corn Adulteration in Brazilian Coffee (Coffea arabica) by Tocopherol Profiling and Near-Infrared (NIR) Spectroscopy. *Journal of Agricultural and Food Chemistry*, 63(49). 10662-10668.
[128] Wongsaipun, S., Theanjumpol P., Kittiwachana S. (2021). Development of a Universal Calibration Model for Quantification of Adulteration in Thai Jasmine Rice Using Near-infrared Spectroscopy. *Food Analytical Methods*, 14(5). 997-1010.
[129] Xie, L. J., Ye X. Q., Liu D. H., Ying Y. B. (2008). Application of principal component-radial basis function neural networks (PC-RBFNN) for the detection of water-adulterated bayberry juice by near-infrared spectroscopy. *Journal of Zhejiang University: Science B*, 9(12). 982-989.
[130] Xu, L., Fu X. S., Fu H. Y., She Y. B. (2015). Rapid Detection of Exogenous Adulterants and Species Discrimination for a Chinese Functional Tea (Banlangen) by Fourier-Transform Near-Infrared (FT-NIR) Spectroscopy and Chemometrics. *Journal of Food Quality*, 38(6). 450-457.
[131] Xu, L., Yan S.-M., Cai C.-B., Yu X.-P. (2013a). Untargeted Detection of Illegal Adulterations in Chinese Glutinous Rice Flour (GRF) by NIR Spectroscopy and Chemometrics: Specificity of Detection Improved by Reducing Unnecessary Variations. *Food Analytical Methods*, 6(6). 1568-1575.
[132] Xu, L., Yan S. M., Cai C. B., Wang Z. J., Yu X. P. (2013b). The feasibility of using near-infrared spectroscopy and chemometrics for untargeted detection of protein adulteration in yogurt: Removing unwanted variations in pure yogurt. *Journal of Analytical Methods in Chemistry*, 2013.
[133] Xu, L., Yan S. M., Cai C. B., Yu X. P. (2013c). Untargeted Detection of Illegal Adulterations in Chinese Glutinous Rice Flour (GRF) by NIR Spectroscopy and Chemometrics: Specificity of Detection Improved by Reducing Unnecessary Variations. *Food Analytical Methods*, 6(6). 1568-1575.
[134] Yang, X., Guang P., Xu G., Zhu S., Chen Z., Huang F. (2020). Manuka honey adulteration detection based on near-infrared spectroscopy combined with aquaphotomics. *LWT*, 132.
[135] Yasmin, J., Ahmed M. R., Lohumi S., Wakholi C., Lee H., Mo C., Cho B. K. (2019). Rapid authentication measurement of cinnamon powder using FT-NIR and FT-IR spectroscopic techniques. *Quality Assurance and Safety of Crops and Foods*, 11(3). 257-267.
[136] Zaukuu, J. L. Z., Bodor Z., Vitalis F., Zsom-Muha V., Kovacs Z. (2019). Near infrared spectroscopy as a rapid method for detecting paprika powder adulteration with corn flour. *Acta Periodica Technologica*, 50. 346-352.

[137] Zhang, L.-G., Zhang X., Ni L.-J., Xue Z.-B., Gu X., Huang S.-X. (2014). Rapid identification of adulterated cow milk by non-linear pattern recognition methods based on near infrared spectroscopy. *Food Chemistry*, 145. 342-348.

[138] Zhao, H.-T., Feng Y.-Z., Chen W., Jia G.-F. (2019). Application of invasive weed optimization and least square support vector machine for prediction of beef adulteration with spoiled beef based on visible near-infrared (Vis-NIR) hyperspectral imaging. *Meat Science*, 151. 75-81.

[139] Zhao, M., O'Donnell C. P., Downey G. (2013). Detection of offal adulteration in beefburgers using near infrared reflectance spectroscopy and multivariate modelling. *Journal of Near Infrared Spectroscopy*, 21(4). 237-248.

[140] Zhu, X., Li S., Shan Y., Zhang Z., Li G., Su D., Liu F. (2010). Detection of adulterants such as sweeteners materials in honey using near-infrared spectroscopy and chemometrics. *Journal of Food Engineering*, 101(1). 92-97.

[141] Ziegler, J. U., Leitenberger M., Longin C. F. H., Würschum T., Carle R., Schweiggert R. M. (2016). Near-infrared reflectance spectroscopy for the rapid discrimination of kernels and flours of different wheat species. *Journal of Food Composition and Analysis*, 51. 30-36.