



REVIEW

Trends in application of NIR and hyperspectral imaging for food authentication

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Abstract

Food fraud can cause damage to consumer health and affect their confidence, destroy brands and generate large economic losses in the industry. Food authenticity allows to identify if food composition, geographical origin, genetic variety and farming system corresponds to what has been declared on the label. Although there are currently standardized methods to identify certain adulterants, the complexity of the food, the complexity of the supply chain and the appearance of new adulterants require the continuous development of analytical techniques to detect food fraud. NIR and Hyperspectral imaging (HSI) in tandem with chemometrics are non-destructive, non-invasive and accurate techniques for food authentication. This review focuses on NIR and HIS approaches to food authentication, including adulteration by substitution, geographical origin and farming system. In this context, the advances in NIR and HSI approaches reported since 2014 are discussed regarding their potential use in food authentication. Both techniques have shown to have efficiency, precision and selectivity to detect adulterants and identify geographic origin, genetic variety and farming system. Portability and remote access are shown as the next step for the industrialization of NIR and HSI devices.

Keywords: food fraud; spectroscopy; discrimination; regression.

1. Introduction

Food authentication has become a growing need throughout the world. Food authentication is aimed at detecting food fraud, which is an illegal action carried out for economic purposes through the adulteration of a food or false information on the label (Barreto *et al.*, 2018; Danezis *et al.*, 2016). This may include genetic variety, geographical origin, processing technology and food composition (Esteki *et al.*, 2018). Also, food authentication is important because food fraud sometimes has unfortunate consequences, for instance, the adulteration of milk powder reported in China in 2008 (Gossner *et al.*, 2009), which caused the death of six children and the hospitalization of thousands of others

(Branigan, 2008). Cases of food fraud cause, in addition to mistrust in the consumer, large economic losses to companies or governments, destroying brands and devaluing the market value of the affected products. For instance, during the pork crisis in Ireland due to dioxin contamination, 1800 jobs were lost, and the cost was estimated at US\$138 million (Kennedy *et al.*, 2009), while it is estimated that the adulteration of olive oil with hazelnut oil causes a loss of 4 million euros per year for the European Union (Ozen and Mauer, 2002).

In order to identify food fraud in food, various techniques have been developed using sophisticated and efficient technologies, which includes chromatographic

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methods (Esteki *et al.*, 2018), proteomics, metabolomics and genomics-based methods (Böhme *et al.*, 2019; Ortea *et al.*, 2016) and spectroscopy techniques (Abbas *et al.*, 2018). This last group includes techniques such as near-infrared spectroscopy (NIR), hyperspectral imaging (HIS), Fourier-transform infrared spectroscopy (FT-IR) and Raman (Figure 1).

NIR is based on the absorption of electromagnetic radiation (light) in a wavelength range between 780 - 2500 nm (Esteki *et al.*, 2018). Each food presents a characteristic spectrum, a fingerprint that allows its identification and differentiation (Barbin *et al.*, 2015). Variations in the absorption of radiation at each wavelength are related to the chemical composition of the food (Rady and Adedeji, 2018). Therefore, factors such as the crop/process conditions, geographical origin, variety or genotype that affect the chemical composition of foods are related with different levels of absorption of radiation at a certain wavelength (Cozzolino, 2016). This allows us, with the help of supervised and unsupervised chemometric methods, to differentiate and classify a wide variety of foods based on the NIR spectral information.

On the other hand, for certain food analysis cases, NIR has not allowed to achieve the expected efficiency, mainly because it is a punctual technique. Hyperspectral imaging (HIS) is a variation of NIR (NIR-HIS), which combines the spectral information obtained from the absorption of the radiation with the spatial information obtained from the image (Kamruzzaman *et al.*, 2016). NIR-HIS provides a greater amount of information than NIR, so one of the key approaches for its possible industrial application is the variable selection and the creation of multispectral models that spend less processing time.



Figure 1. NIR and hyperspectral imaging to detect food fraud.

This review shows a summary of the most recent applications of NIR and NIR-HIS for food authentication, which includes: geographical origin, genotype, genetic variety and adulteration by addition/substitution.

2. 2. Recent applications of NIR and NIR-HIS for food authentication

2.1 Vegetable oil

Vegetable oils are one of the foods most susceptible to adulteration, both by addition and by false information regarding their geographical origin (Table 1). For instance, The Rapid Alert System for Food and Feed (RASFF) exposed a food fraud case in sunflower oil with high levels of mineral oil on 23 April 2008 (Picouet *et al.*, 2018). This led to Picouet *et al.* (2018) to develop a technique to detect “at-line” mineral oil in sunflower oil, using a portable NIR coupled with a reflection probe, coupled with an immersion probe and a prototype of a multichannel Quasi Imaging Visible NIR spectrometer coupled to an immersion probe. The prototype has been useful to detect adulteration at levels above 2.5%. However, portable NIR coupled to reflection probe to be more efficient (R^2_{cal} better than 0.99), achieving pure samples of sunflower oil with a probability of 98.5%, and samples adulterated with mineral oil with a probability of 95%. Nevertheless, the authors conclude that detection of adulterated samples below 0.5% is difficult using NIR, therefore, chromatographic techniques should be used to confirm the fraud.

On the other hand, NIR in transmission and transmittance modes combined with SIMCA classifier allowed detect lard in palm oil with accuracy > 0.95 (Basri *et al.*, 2017). Also, the quantitative analyses were performed by PLS coupled with variable selection based on cumulative adaptive reweighted sampling (CARS) (Li *et al.*, 2009). CARS allowed identify important wavelength interacted with the fat and oil chemical structure, being used for building robust prediction model ($R^2_p > 0.99$). CARS-PLS and CARS-ECR (elastic component regression) also showed good results for identify adulterated samples of sesame oil with different oil (see Table 1) (Chen *et al.*, 2018). Therefore, this selection variable method should be tested in other oil type with different adulterants or different geographical origin.

One of the vegetable oils with the highest risk of adulteration is olive oil (van Ruth *et al.*, 2018) established that after the spice supply chain, the olive oil supply chain is the most susceptible to food fraud, mainly

related on fraud factors of (1) fraud detectability in raw material and (2) fraud detectability in final product, (3) historical evidence of fraud, (4) valuable components or attributes and (5) level of competition branch of industry. For this reason, NIR spectroscopy has been a useful tool for the detection of olive oil adulteration. *Azizian et al. (2016)* developed PLS models using information from the FT-NIR to predict the content of various compositional parameters of olive oil and relate it to its authenticity. From 66 samples, 50 from California (USA), 15 from different European countries and 1 from Spain, only 23 met the authenticity requirements. FT-

NIR allowed in less than 5 min time to identify the samples and assign them to different groups based on their composition. Similar results were found to detect extra-virgin olive oil adulterated with edible oils using FT-NIR spectral data combined with SIMCA classifier (*Karunathilaka et al., 2016*) and for olive oil blended with edible oil using NIR coupled by SVM (*Wu et al., 2016*). Also, NIR was very efficient to detect soybean oil (*Mendes et al., 2015*), different edible oils (*Mossoba et al., 2017*) and refined and mild deodorized olive oils (*Wójcicki et al., 2015*) in extra-virgin olive oil.

Table 1
NIR and HIS to vegetable oil authentication

Oil type	Fraud control	Instrument	Chemometrics	Statistical parameters	Reference
Sunflower oil	Mineral oil	NIR on mode reflectance	Back ground correction + baseline correction + 1 st derivate + MSC/PLS	R ² p=0.99; RMSEP=0.23%	<i>Picouet et al. (2018)</i>
		Prototype of a multichannel Quasi Imaging Visible NIR spectrometer	Background division + 1 st derivate/PLS	R ² p=0.91; RMSEC=1.0%	
Palma oil	Lard	NIR in transmission mode	SIMCA CARS-PLS	Precision=1.0 Specificity=1.0 Sensitivity=0.2 R ² p=0.99; RMSEC=0.33%	<i>Basri et al. (2017)</i>
		NIR in transreflectance mode	SIMCA CARS-PLS	Precision=1.0 Specificity=1.0 Sensitivity=0.4 R ² p=0.99; RMSEP=0.41%	
Sesame oil	Authenticity	NIR in absorbance mode	CARS-PLS CARS-ECR (Elastic component regression)	RMSEC=0.0245; RMSEP=0.055 RMSEC=0.0188; RMSEP=0.039	<i>Chen et al. (2018)</i>
Olive oil	Authenticity	UV-VIS-NIR	SBS-PLS (Stimulated Brillouin scattering)	R ² p=0.99	<i>Shi et al. (2019)</i>
Extra virgin olive oil	Soybean oil	NIR	PLS	R ² p=0.99 RMSEP=1.76	<i>Mendes et al. (2015)</i>
Extra virgin olive oil	Refined and mild deodorized olive oil	NIR	PCR	R ² p=0.98 RMSEP=2.7 RDP=8.5	<i>Wójcicki et al. (2015)</i>
Extra virgin olive oil	Geographical origin	NIR	PLS-DA	Overall classification=100%	<i>Jiménez-Carvelo et al. (2019)</i>
Extra virgin olive oil	Authenticity	FT-NIR	PLS	R ² p>0.95	<i>Mossoba et al. (2017)</i>
Extra virgin olive oil	Authenticity	FT-NIR	SIMCA	Overall classification=100%	<i>Karunathilaka et al. (2016)</i>
Olive oil	Authenticity	NIR	SVM	Overall classification=93 - 100%	<i>Wu et al. (2016)</i>
Extra virgin olive oil	Geographical origin	NIR	PLS-DA	R ² c=0.93 RMSEC=0.128	<i>Peršurić et al. (2018)</i>
Extra virgin olive oil	Geographical origin	NIR	SIMCA	Correct classification= 89.55 - 98.50%	<i>Laroussi-Mezghani et al. (2015)</i>
Olive oil	Geographical origin	NIR	LDA	Correct classification= 98.5 - 100%	<i>Forina et al. (2015)</i>

In contrast, UV-VIS-NIR (in wavelengths 670 and 455 nm) combined with stimulated Brillouin scattering (SBS) achieved to detect olive oil adulteration (Shi *et al.*, 2019). SBS is an inelastic dispersion process that is presented by the fluctuation of the density of the acoustic sources in the medium, which allows to relate it to the properties of the density and refractive index (Shi *et al.*, 2012). These olive oil properties change with adulteration with other oils, and can be used as an efficient method to separate between pure and adulterated samples. The method must be extended for analysis of oils of species with a high index of polyunsaturated fatty acids, as well as their mixtures, because the instability of these oils constantly complicates their identification.

The determination of geographical origin of olive oil is essential for the traceability of the products and because the composition of the product is affected by their process conditions (Nenadis and Tsimidou, 2017; Wang *et al.*, 2016). NIR combined with PLS-DA was more efficient than fluorescence excitation-emission matrix spectroscopy technology to classify Argentinian extra-virgin olive oil (Jiménez-Carvelo *et al.*, 2019). Similar results were found for NIR/SIMCA to classify Tunisian extra-virgin olive oil (Laroussi-Mezghani *et al.*, 2015), NIR/PLSDA to classify Croatian extra-virgin olive oil (Peršurić *et al.*, 2018) and NIR/LDA to classify Italian olive oil (Forina *et al.*, 2015) according geographical origin.

What is questionable, perhaps, is the need for more representative and corroborative sampling. The time storage of oils, the type of olive cultivar and the process kind carried out for oil extraction must be considered (Binetti *et al.*, 2017). These factors affect the composition of the oil, so the differences may be given not by the culture conditions of a specific place (geographical origin), but may be dependent on other factors. For instance, if different cultivars are used, it is very likely that the variations in composition are related to the type of cultivar, so the results cannot be conclusive to differences related to geographical origin.

2.2 Coffee

Coffee is one of the most consumed food species in the world. Among the varieties with greater economic importance is the Arabica coffee (*Coffea arabica*) and Robusta coffee (*Coffea canephora*) varieties (Thorburn-Burns *et al.*, 2017). Both species have differentiated organoleptic characteristics, the most

appreciated being the Arabica variety, with a higher market price compared to the robust variety. These variations in price are related to the most delicate form of Arabica coffee production, growing at heights between 600 - 2000 m (Barbin *et al.*, 2014; Caporaso *et al.*, 2018). Therefore, the identification of the variety of coffee beans represents a very important research focus. In addition, because coffee is consumed in powder, it can be adulterated at various stages of its supply chain, using lower value coffee or other food waste (i.e. barley). Table 2 summarized the last research in the NIR and HIS application for coffee authentication.

Bona *et al.* (2017) used support vector machine (SVM) to compare NIR and FT-IR for classification Arabica coffee according geographical origin in Brazil. SVM in tandem with NIR spectral data allowed to classify correctly (100%) Arabica coffee samples. Similar results (sensitivity and specificity = 1.0) were found for identify geographical origin and genotype origin of Arabica coffee using PLS-DA in tandem with NIR (Marquetti *et al.*, 2016). For its part, for Robusta coffee beans, FT-NIR coupled with self-organizing map (SOM) allowed to identify and classify Robusta coffee genotype origin (100% correct classification) (Luna *et al.*, 2017). After, in Brazil, a new research compared proton transfer reaction mass spectrometry (PTR-MS) and NIR to classify Arabica and Arabica/Robusta (rate no informed) coffee according geographical origin (5 cities) and farming system (conventional and organic) (Monteiro *et al.*, 2018). NIR coupled with PLS-DA obtained a correct classification > 80% for identify farming system, which is an advantage compared with PTR-MS due to low price, rapid analysis and minimal sample preparation. More recently, in inter-laboratory analyses was confirmed the FT-NIR potential for classify Arabica and Robusta coffee from different geographical origin (2 continents, 9 countries) (Girauda *et al.*, 2019). PLS-DA was a chemometric used to develop efficient classification models (correct classification > 93%) for classify coffee beans according continent origin and country origin. At same time, the results were confirmed for two laboratories and no significant difference ($p < 0.05$) was found, which allows to create more reliable and robust analytical methods.

Variety identification (Robusta or Arabica) in green or roasted beans is important for food fraud control. Roasting coffee is an important stage for its consumption,

because roasting process intensifies the organoleptic properties of coffee beans. However, roasting also disguises the appearance of coffee beans, making identification difficult. (De Luca *et al.*, 2016) studied the possibility of using NIR combined with the PLS-DA or SIMCA classifiers to identify the variety (Arabica or Robusta) of roasted coffee. Both classifiers proved to be efficient in differentiating between coffee varieties regardless of coffee origin (Table 2). On the other hand, portable NIR was used successfully to identify blends of Arabica coffee with Robusta coffee (in different roasting levels), corn, peels and sticks (Correia *et al.*, 2018). PCA and PLS were chemometrics employed to identify the adulterated samples, obtaining a quantification limit (LOQ) of 5 – 8% w/w. Similar results ($R^2p = 0.97$) were found using FT-NIR spectral

data coupled with PLS to detect Robusta coffee in Arabica coffee (Bertone *et al.*, 2016).

Hyperspectral imaging (HIS) is powerful technique for coffee beans identification and characterization (Caporaso *et al.*, 2018; Zhang *et al.*, 2013). Due to a big data provided by HIS, a variable selection to build a multispectral imaging system is essential for industrial application (Amigo *et al.*, 2013). For Arabica and Robusta coffee discrimination was tested sparse methods (sPCA + KNN and sPLS-DA) using HIS data (Calvini *et al.*, 2015). The sparse methods allow to perform variable selection at the same time as classification, giving parsimonious models. Both sPCA + KNN and sPLS-DA converged to the same important wavelengths, however, the analysis time for sPCA + KNN was higher (13.5 s) than sPLS-DA (< 0.1 s).

Table 2
NIR and HIS to coffee beans authentication

Coffee variety	Fraud control	Instrument	Chemometrics	Statistical parameters	Reference
Arabica	Geographical origin	NIR	SVM	Sensitivity=1.0 Specificity=1.0	Bona <i>et al.</i> (2017)
Arabica	Authenticity	Portable NIR	PCA and PLS	$R^2p=0.96 - 0.99$ RMSEP=2.8 – 6.6%	Correia <i>et al.</i> (2018)
Arabica	Blends with Robusta coffee	FT-NIR	PLS	$R^2p=0.97$ RMSEP=4.3%	Bertone <i>et al.</i> (2016)
Robusta and Arabica	Geographical origin	FT-NIR	PLS-DA	Correct classification > 93%	Giraud <i>et al.</i> (2019)
Arabica and Arabica/Robusta blend	Geographical origin	NIR	PLS-DA	Correct classification > 61%	Monteiro <i>et al.</i> (2018)
	Farming system	NIR	PLS-DA	Correct classification > 80%	
Arabica and Robusta roasted	Variety identification	NIR	PLS-DA	Correct classification = 100%	De Luca <i>et al.</i> (2016)
		NIR	SIMCA	Sensitivity and specificity > 90%	
Robusta and Arabica	Variety identification	NIR-HIS	sPCA + kNN	Efficiency prediction (test set) = 100% Efficiency prediction (test image) = 86.9%	Calvini <i>et al.</i> (2015)
		NIR-HIS	sPLSDA	Efficiency prediction (test set) = 100% Efficiency prediction (test image) = 80.2%	
Robusta and Arabica	Variety identification	NIR-HIS	PLS-DA (4 variables)	Efficiency prediction (test set) = 94.9% Efficiency prediction (test image) = 74 - 92.2%	Calvini <i>et al.</i> (2017)
		NIR-HIS	PLS-DA (32 variables)	Efficiency prediction (test set) = 100% Efficiency prediction (test image) = 71 – 92.1%	
		NIR-HIS	sPLS-DA (2 variables)	Efficiency prediction (test set) = 100% Efficiency prediction (test image) = 83.9 – 93.1%	
Robusta and Arabica	Variety identification	NIR-HIS	Extreme Learning Machine	Correct classification = 93.5%	Bao <i>et al.</i> (2015)
Robusta and Arabica	Variety identification	NIR-HIS	SVM	Correct classification = 98%	Zhang <i>et al.</i> (2018)
Arabica	Geographical origin	NIR	PLS-DA	Sensitivity = 0.75 – 1.0 Specificity = 1.0	Marquetti <i>et al.</i> (2016)
	Genotype origin	NIR	PLS-DA	Sensitivity = 0.75 – 1.0 Specificity = 0.93 – 1.0	
Robusta	Genotype origin	FT-NIR	PLS-DA	Correct classification = 82.9%	Luna <i>et al.</i> (2017)
		FT-NIR	SIMCA	Correct classification = 99.6%	
		FT-NIR	SOM	Correct classification = 100%	
		FT-NIR	SVM	Correct classification = 99.6%	

After, the same research group used four commercial filters: 1150 nm related to C-H aromatic second overtones, 1200 and 1250 nm C-H aliphatic second overtone and 1400 nm O-H first overtone of aliphatic, to build multispectral model from the data obtained from a hyperspectral image (Calvini *et al.*, 2017).

The results (see Table 2) suggest that the multispectral model (4 variables) in tandem with filters (individual) + PLS-DA or filters (combined) + sPLS-DA are as efficient as the models built using full spectrum (150 variables). However, the analysis time is considerably reduced, which is important for its online application. In the pixel-to-pixel image classification, there is a shape effect of the coffee beans that are most noticeable in the prediction set. Although, in general, the classification was correct (100%), new investigations can be carried out to correct the shape effects, allowing a better prediction in each pixel of the image. These results were better to those found in previous works using NIR-HIS combined with Extreme Learning Machine (correct classification = 93.5%) (Bao *et al.*, 2015) and NIR-HIS coupled with SVM (correct classification = 98%) (Zhang *et al.*, 2018) using full spectra.

2.3 Cereals

Grains of cereals, wheat, rice, barley, oats; and its derivatives, such as derived flour, are important ingredients for the most important staple foods throughout the world, since they make foods such as breads, pastas, cakes and cookies (Murniece and Straumite, 2014). For this, the risk for the illicit activity associated with cereals and derived products, are part of a big problem because of the impact for everyone. Appropriate prevention measures can only be implemented if the nature and type of illegal activity is understood (Tähkäpää *et al.*, 2015). Therefore, this research aims to determine and analyze the extent of reported cases of food adulteration in cereals and products to identify potential trends and frame the development of future empirical research in this area. In this case, optical techniques arise, such as the use of NIR and hyperspectral images, as efficient methods to control the quality of these foods.

The adulteration of wheat flour using cheaper flours is a common fraud case. HSI overcomes the difficulties of the heterogeneity of the sample, allowing to efficiently detect flours of different grains. Methods based on HSI with multivariate analysis such as multivariate statistical

process control method (MSPC) (Verdú *et al.*, 2016) and PLS-DA (Ziegler *et al.*, 2016) allowed to discriminate between pure wheat samples and adulterated samples.

In many countries, including China, Japan and South American countries, rice (*Oryza sativa* L.) is one of the staple foods of their daily diet (Maione and Barbosa, 2018). Rice is a source of vitamins, minerals, fiber and many essential elements (da Silva *et al.*, 2018; Dang and Vasanthan, 2019). The determination of the geographical origin and variety of rice has been an increasing research line in recent years, especially in Asia region (Maione and Barbosa, 2018). And, although the analysis of isotopes and minerals have been quite decisive for the authentication of rice (Mo *et al.*, 2017), NIR spectroscopy is shown as a promising technique (Table 3).

NIR coupled with support vector data description (SVDD) was used to verify the black rice authenticity (Chen *et al.*, 2018). SVDD showed a best performance (100% specificity and 94.2% sensitivity to identify authentic black rice) compared with k-nearest neighbor data description (KNNDD) and GAUSS method. This study should be extended for all rice varieties and more chemometrics as PLS-DA and SIMCA must be used. On the other hand, diverse wavelength selection methods should be tested in order to reduce analysis time by creating multispectral models.

In other research, the NIR potential was tested to identify and classify rice according farming system: organic or conventional (Xiao *et al.*, 2018). PCA and PLS were used to analyze NIR spectral data. PLS showed a good performance ($R^2_{cv}=0.8430$ and $RMSECV=0.1992$) to identify organic and conventional rice. However, the PLS was constructed using pure samples and no wavelength selections was performed. Then, PLS-DA, KNN or SIMCA probably present a better discrimination capacity to classify rice according farming system, and new research should be drive in this sense.

Hyperspectral imaging allowed identify and classify rice from different China's regions (Sun *et al.*, 2017). The spectral, texture and morphological features obtained of rice's hyperspectral imaging were combined with SVM for classify rice according geographical origin. The features were tested individually and combined, being the spectral-texture-morphological model (based on 9 important wavelengths) better (correct classification = 91.67%) than other models.

Table 3
NIR and HIS applied to cereal products authentication

Product	Fraud control	Instrument	Chemometrics	Statistical parameters	Reference
Wheat	Sorghum	HSI	Control of Multivariate Statistical Process (MSPC)	R ² p=0.95	Verdú <i>et al.</i> (2016)
	Oat			R ² p=0.97	
	Corn			R ² p=0.99	
Oat	Barley Wheat Rye	HIS	PCA-PLSDA	Correct classification = 0.96	Erkinbaev <i>et al.</i> (2017)
Avatar Wheat	Common wheat	HIS	FMCIA-PLSR	R ² p=0.97 RMSEP=0.038	Su and Sun (2017)
	Cassava flour			R ² p=0.98 RMSEP=0.026	
	Corn flour			R ² p=0.97 RMSEP=0.036	
Organic spelt (<i>Triticum spelta</i> L.)	Rye	HIS	PLSR	R ² p=0.96	Su and Sun (2016)
	Organic wheat			R ² p=0.97	
	Common spelt		R ² p=0.93		
	Rye		R ² p=0.96		
	Organic wheat		MLR	R ² p=0.97	
Rice	Geographical origin	HIS	SVM	R ² p=0.9167	Sun <i>et al.</i> (2017)
Rice	Geographical origin	HIS	PLS-DA	Correct classification = 99%	Mo <i>et al.</i> (2017)
Wheat grains	Geographical origin	NIR	LDA	Correct classification = 82%	Zhao <i>et al.</i> (2013)
			PLS-DA	Correct classification = 92%	
Wheat grains	Geographical origin	NIR	PCA-PLS	Correct classification = 85%	Zhao <i>et al.</i> (2014)
Corn	Geographical origin	NIR	PLS-DA	Correct classification = 87.9%	Zhou <i>et al.</i> (2015)
Wheat Canada Western Red Spring (CWRS)	Barley, Canola, Maize Flaxseed / Oats / Rye / Soybean Broken Kernels / Buckwheat / Chaff / Stones / Wheat Spikelets / Wild Oats Deer Droppings / Rabbit Droppings	NIR - HIS	SNV / K-Nearest Neighbors / Naive Bayes	Correct classification = 100 %	Ravikanth <i>et al.</i> (2015)
Durum wheat	Common wheat	HIS - NIR	PLS - DA	Sensibilidad = 88.3	Vermeulen <i>et al.</i> (2018)
Wheat	Authenticity	NIR	PLS - DA	Sensibilidad = 90 Especificidad = 100 Exactitud = 95	Ziegler <i>et al.</i> (2016)
Cooked millet flour	Soybean flour	HIS - NIR	LS - SVM	Correct classification = 98.30%	Shao <i>et al.</i> (2018)
Lentils	Geographical origin	FT - NIR	PLS - DA	RSQ = 0.96 RMSECV = 0.40	Revilla <i>et al.</i> (2019)

The correct sample collection is essential to develop an analysis method based on spectral information, which should be represent the variability studied (i.e. geographical origin). For instance, if the aim is to differentiate by geographical origin, factors such as genetic variety, genotypes (cultivars) and year of harvest must be controlled.

2.4 Meat and fish

Adulteration in meat and meat products with undeclared animal species has generated concern among consumers, because these meats are considered an edible (i.e. horse meat in USA) or due to social taboos (i.e. pork meat in Mulsim and Jewish communities) (Boşacı *et al.*, 2014; Monahan *et al.*, 2018; Nakyinsige *et al.*,

2012). Perhaps the greatest likelihood of food fraud is found in meat products. Because the meat processing removes external morphological features of a muscle, which makes it difficult to identify the meat species in the processed product (Sentandreu and Sentandreu, 2014). Due to the dynamism of the meat industry, fast, reliable and robust methods are needed that allow the authentication of meat and meat products (Amaral *et al.*, 2016; Kumar and Chandrakant-Karne, 2017). NIR and HIS are presented as powerful, non-destructive, non-invasive, fast and reliable technologies for meat authentication (Aredo *et al.*, 2017; Cheng *et al.*, 2017). Table 4 shows the last research focused in meat and fish authentication.

The taste and texture of the meat varies depending on the type of muscle consumed, and many times various undeclared muscles are mixed with fraudulent economic motivations. Hyperspectral images of Lamb muscles: *Longissimus dorsi*, *Psoas major*, *Semimembranosus* and *Semiten-dinosus*, were acquired in order to classify according muscle type (Sanz et al., 2016). After testing different machine learning techniques, the linear Least Mean Squares (LMS) classifier showed the best result (96.67% correct classification). Nolasco et al. (2018) studied the use of NIR to classify different chicken parts: drumstick, breast and thigh. The linear discriminant analysis (LDA), random forest (RF), and support vector machine (SVM) algorithms were used and a correct classification of 97.5% was achieved. It should be noted that this research was conducted using a portable NIR, which is more attractive and less expensive industrially.

Rady and Adedeji (2018) studied the adulteration of beef with chicken or pork and with vegetable protein using Vis-NIR-HIS and NIR-HIS. Both sensors (Vis-NIR-HIS and NIR-HIS) showed to be efficient to classify pure samples of beef, chicken, pork, texturized vegetable protein (TVP) and wheat gluten (WG) (100% correct classification) and adulterated samples (96% using selected wavelengths). The adulterant identification was more difficult, but acceptable (69 – 100% correct classification). Vis-NIR-HIS in selected wavelengths was more efficient [r(RDP)] for predict adulterant concentration in minced beef: 0.85 (1.77) for pork, 0.86 (1.95) for TVP, 0.86 (1.98) for chicken, 0.86 (1.87) and 0.87 (1.64) for WG. In addition, Vis-NIR-HIS coupled with PLS regression allowed to quantify duck meat concentration in minced lamb ($R^2_p = 0.98$) (Zheng et al., 2019).

On the other hand, NIR coupled with one-class classifier variant of the partial least squares method (OCPLS) and the soft independent modeling of class analogy (SIMCA) allowed to classify ground meat according specie origin (lamb, beef and pork) (Pieszczyk et al., 2018). Therefore, it is possible that NIR coupled with any of these two classification techniques (SIMCA or OCPLS) is appropriate and feasible to identify ground beef according to its species at industrial level. Later, the potential of NIR to identify and classify beef and lamb meat adulterated with pork, chicken, Lidia breed cattle or foal was studied (López-Maestresalas et al., 2019). NIR spectral data in tandem with PLS-DA achieved a correct classification between

78.95 - 100% in validation set. The adulteration of lamb and beef with chicken meat was more difficult to access. However, the Lidia breed cattle and foal in minced beef could be detected at levels of adulteration above 2% and 1%, respectively. These results were better than those found to identify and quantify turkey meat in minced beef (fresh, frozen-thawed and cooked) using FT-NIR with PLS-DA (Sensitivity = 0.84; specificity = 0.76) (Alamprese et al., 2016). On the other hand, it was possible identify and classify (Correct classification = 94.2 – 100%) beef steaks according their ageing time (3, 7, 14 and 21 days *post mortem*) using Vis-NIR spectral data combined with PLS-DA (Moran et al., 2018). Also, the authenticity of Italian Valle d'Aosta Arnad Protected Designation of Origin (PDO) lard can be determine using NIR spectral data in tandem with PLS-DA (Sensitivity and Specificity = 94.4%), although with less precision than using volatile compound (VOC) or fatty acid (FA) analyses (Sensitivity and Specificity = 100%) (Chiesa et al., 2016). For its part, FT-NIR in tandem with SVM allowed to analyze and classify veal sausage adulterated with pork and pork fat (10 – 50% w/w) (Schmutzler et al., 2015). The results found in this work are quite relevant, since the method developed in the laboratory was tested in *industrial and on-site instrumental setups*, analyzing them successfully through their plastic packaging (75 - 100% correct classification).

Currently, the fish production and marketing chain has been internationalized, with fish exported from developing to developed countries. NIR spectroscopy in tandem with SIMCA was used to classify tilapia fillets according to their geographical origin (China) (Liu et al., 2015).

The results showed that the NIR spectral information is able to classify, acceptably (Correct classification = 75 - 85%), between tilapia fillets from different regions of China (Guangdong Province, Hainan Province, Guangxi Province and Fujian Province). On the other hand, Vis-NIR-HIS was tested for classify fresh from cold-stored (4 °C for 7 days) and frozen-thawed (-20 °C and -40 °C for 30 days) grass carp fish fillets (Cheng et al., 2015). SIMCA, PLS-DA, least squares-support vector machine (LS-SVM) and probabilistic neural network (PNN) classifiers were tested using full and important wavelengths (446, 528, 541, 596, 660, 759 and 970 nm).

Table 4
NIR and HIS to meat and fish authentication

Meat product	Fraud control	Instrument	Chemometrics	Statistical parameters	Reference
Lamb	Muscle discrimination	Vis-NIR HIS	Linear least Mean Squares (LMS)	Correct classification = 96.67%	Sanz <i>et al.</i> (2016)
Chicken	Muscle discrimination	NIR	LDA Random Forest SVM	Correct classification = 97.5%	Nolasco <i>et al.</i> (2018)
Beef	Adulteration	VIS-NIR HIS	SVM PLS	Overall classification = 76 - 95% R ² p = 0.53 – 0.86 RMSEP = 0.17 – 1.36	Rady and Adedeji (2018)
		NIR-HIS	SVM PLS	Overall classification = 81 - 95% R ² p = 0.53 – 0.86% RMSEP = 0.26 – 0.55%	
Ground meat	Specie identification	NIR	SIMCA	Sensitivity = 96 - 100% Specificity = 80 – 99%	Pieszczyk <i>et al.</i> (2018)
		NIR	one-class classifier variant of the partial least squares method (OCPLS)	Sensitivity = 95 - 100% Specificity = 73 – 99%	
Lamb and Beef	Adulteration	NIR	PLS-DA	Correct classification = 78.95 – 100%	López-Maestresalas <i>et al.</i> (2019)
Lamb	Adulteration	Vis-NIR-HIS	PLS	R ² p = 0.98 RMSEP = 2.51%	Zheng <i>et al.</i> (2019)
Veal sausage	Adulteration	FT-NIR	SVM	Correct classification = 75 – 100%	Schmutzler <i>et al.</i> (2015)
Beef steaks	Ageing time	Vis-NIR	PLS-DA	Correct classification = 94.2 – 100%	Moran <i>et al.</i> (2018)
Lard	Authenticity	NIR	PLS-DA	Sensitivity and specificity = 94.4%	Chiesa <i>et al.</i> (2016)
Fresh, frozen-thawed and cooked minced beef	Adulteration	FT-NIR	PLS-DA PLS	Sensitivity = 0.84 Specificity = 0.76 R ² p = 0.884 RMSEP < 10.8%	
Pork muscle	Fresh and frozen-thawed	Vis-NIR-HIS	Gray-level-gradient co-occurrence matrix (GLGCM) + probabilistic neural network (PNN)	Correct classification = 90.91 – 93.14%	Pu <i>et al.</i> (2015)
Pork muscle	Fresh and frozen-thawed	Vis-NIR-HIS	PLS-DA based on fused variables combining spectra at the optimal wavelengths and textures	Correct classification = 97.73%	Ma <i>et al.</i> (2015)
Chicken	Farming system	Vis-NIR-HIS	Gray-level-gradient co-occurrence matrix (GLGCM) + radial basis function-support vector machine (RBF-SVM)	Correct classification = 93.33%	Xiong <i>et al.</i> (2015)
Tilapia fillets	Geographical origin	NIR	SIMCA	Correct classification = 75 – 85%	Liu <i>et al.</i> (2015)
Salmon	Farming system	Vis-NIR-HIS	SVM	Correct classification = 98.2%	Xu <i>et al.</i> (2017)
		NIR-HIS	SVM	Correct classification = 92.7%	
Carp	Fresh, cold-stored, frozen-thawed	Vis-NIR-HIS	LS-SVM	Correct classification = 90 – 100%	Cheng <i>et al.</i> (2015)

1st derivate pre-processing technique and LS-SVM showed the best performance using full wavelengths (94.29% correct classification) and important wavelengths (91.43% correct classification). Later, (Xu *et al.*, 2017) studied and compared the potential of computational vision and Vis-NIR-HIS for classify salmon according farming system: organic and conventional. Vis-NIR-HIS combined with SVM was more successful (98.2% correct classification) than using computational vision (83.6% correct classification using PLS-DA) or NIR-HIS (92.7% correct classification using SVM) to classify salmon.

2.5. Honey

Honey is probably one of the most complex and consumed natural food (Pita-Calvo *et al.*, 2017). Bees (*Apis mellifera*) collect nectar, plant secretions or excretions of plant-sucking insects to produce honey, after complex enzymatic process. Honey is a complex mixture of carbohydrates (70-80% w / w), water (10-20% w / w) and a large number of minor components (Ouchemoukh *et al.*, 2007). Fructose/glucose and fructose/glucose disaccharide are the main carbohydrates in honey (65-80% w/w) (de la Fuente *et al.*, 2006). Therefore, a common adulteration

practice is through mislabeling and mixing sugar syrup and lower-quality honeys or production honey using sugar instead of nectar.

In this context, NIR is probably a most sensitive spectroscopy technique to detect honey fraud (Naila *et al.*, 2018). However, some studies show the efficiency of hyperspectral images to identify adulteration and the origin of honey. Table 5 summarizes the works that apply NIR and hyperspectral images to determine honey authenticity. The chemical composition and nutritional properties of honey make it a healthy and desired food. Therefore, its market value is more expensive than common sweeteners such as sugar beet, cane, inverted syrups and syrups with high fructose content (Pita-Calvo *et al.*, 2017). But, the adulteration of honey with inverted syrups or high fructose syrups is usually difficult to detect, because they mimic the sucrose-glucose-fructose profile of honey (Paradkar and Irudayaraj, 2002). NIR is presented as a potential tool to identify adulterated honey with high fructose syrups. Discriminant methods are main chemometrics to classify unknown honey samples into clusters on the basis of similarities (Sivakesava and Irudayaraj, 2001). NIR spectral data in tandem with

LDA allowed to identify high fructose corn syrup in honey (CCR = 100%) and to predict adulterant concentration (Ferreiro-González *et al.*, 2018). For high fructose corn syrup and maltose syrup adulterants, a multispectral model based on NIR data combined with CARS/PLS-Da achieved high precision (CCR = 88.3%) (Li *et al.*, 2017). CARS allows to select important wavelengths, to build multispectral model for on-line applications (Li *et al.*, 2009). However, multispectral models must be equal or more accurate than models using whole spectrum. On the other hand, NIR spectral data obtained using fiber optic immersion probe (transmittance mode) was used to build PLS models for detecting accurately high fructose corn syrup in honey (RMSECV = 1.48; R²CV = 0.987) (Bázár *et al.*, 2016). Later, Başar and Özdemir (2018) built regression models to detect beet sugar and corn syrup in honey. Two regression chemometrics was tested: (1) PLS and (2) Genetic-algorithm-based inverse least squares (GILS) (Karaman *et al.*, 2009). Both showed similar accuracy to predict adulterant concentration, but multispectral model can be constructing for on-line applications.

Table 5
NIR and HIS to Honey authentication

Fraud control	Instrument	Chemometrics	Statistical parameters	Reference
Floral origin	VIS/NIR-HSI	Radial basis function (RBF) SVM Random forest	Accuracy = 94% Accuracy = 93% Accuracy = 93%	Minaei <i>et al.</i> (2017)
Floral origin	NIR	PLS	RPD = 2.1 – 3.5	Escuredo <i>et al.</i> (2015)
Botanical origin	NIR	PLS-DA	Accuracy = 85 – 100%	Gan <i>et al.</i> (2016)
High fructose corn syrup	VIS/NIR	LDA PLS	Correct classification = 100% R ² p = 0.98 RMSEP = 4.71%	Ferreiro-González <i>et al.</i> (2018)
High-fructose corn syrup	NIR	CARS/PLS-DA	Correct classification = 86.3%	Li <i>et al.</i> (2017)
Maltose syrup	NIR	CARS/PLS-DA PLS	Correct classification = 96.1% R ² p = 0.90 – 0.98 RMSEP = 1.78 - 4.04%	Li <i>et al.</i> (2017)
Fructose-glucose	VIS/NIR - HSI	ANN SVM LDA Fisher Parzen	Accuracy = 95% Accuracy = 92% Accuracy = 90% Accuracy = 89% Accuracy = 84%	Shafiee <i>et al.</i> (2016)
High fructose corn syrup	NIR in transreflectance mode	PLS	R ² cv = 0.98 RMSECV = 1.48	Bázár <i>et al.</i> (2016)
Glucose and fructose	Benchtop NIR Portable NIR Mobile NIR	PLS-DA PLS-DA PLS-DA	Accuracy = 96.9% Accuracy = 93.7% Accuracy = 87.5%	Guelpa <i>et al.</i> (2017)
Beet sugar and corn syrup	NIR	Genetic-algorithm-based inverse least squares (GILS) Partial least squares (PLS)	RMSEP= 0.90 – 2.19% R ² p = 0.99 RMSEP= 1.18 – 2.89% R ² p = 0.97 – 0.99	Başar and Özdemir (2018)
Jaggery adulterants	NIR	PLS	RMSEC= 0.0075 R ² c = 0.99	Kumaravelu and Gopal (2015)
Glucose	NIR	PLS	RMSECV= 4.52% R ² cv = 0.85 RPD = 2.53	Mouazen and Al-Walaan (2014)

For detecting glucose and fructose in adulterated honey sample, more one of discriminant analysis was tested accurately. PLS-DA was selected as chemometrics tool to build discriminant models for authenticity of South African honey based on prediction of glucose and fructose concentrations (Guelpa *et al.*, 2017). This work shows that the loss of precision is minimal compared to portable NIR with table NIR, which industrially is quite important. Similar results was showed for glucose (Mouazen and Al-Walaan, 2014) and jaggery (Kumaravelu and Gopal, 2015) adulterants in honey using NIR spectral data in tandem with PLS regression. On the other hand, VIS/NIR-HSI showed a good performance to detect honey adulterated with fructose and glucose using SVM, LDA and ANN (Shafiee *et al.*, 2016). Chemical maps based on ANN model were built for visual identification of sample adulteration. However, the large amount of information offered by HSI makes its industrial application difficult to implement. New works should be directed to identify the wavelengths important for the identification of each adulterant. Thus, the implementation of HSI in the honey supply chain is less costly and easier to manage. Honey can be unifloral or multifloral. Unifloral honey is more expensive, due to its low production, therefore its susceptibility to adulteration is higher. For this, there is a protected designation of origin (PDO) and protected geographical indication (PGI) for honey (Cajka *et al.*, 2009), and its identification is economically important. For more information on denomination of origin regulations, diverse analytical methods for authentication and analysis of honey composition you can access the reviews of Pita-Calvo *et al.* (2017), Trifković *et al.* (2017), Soares *et al.* (2017), Naila *et al.* (2018), Wu *et al.* (2017), among others. Pollen types (*Castanea*, *Eucalyptus*, *Rubus* and *Erica*) related with honey floral (or botanical) origin was successfully determinate using NIR in tandem with PLS (Escuredo *et al.*, 2015). Similar results (CCR=100%) for botanical origin was reported using NIR and iPLS (Gan *et al.*, 2016) (Table 4). Later, VIS/NIR-HIS combined with radial basis (RBF), SVM and Random forest showed similar accuracy for detect honey floral origin (Minaei *et al.*, 2017). Since hyperspectral imaging is a combination of machine vision and spectroscopy, the adulterant distribution can be observed in sample, and their use could be expanded to associate chemical

image with adulterant or adulterant/honey features.

3. Data fusion in food authentication

The data fusion strategy has allowed obtaining, in many cases, more precise and conclusive results than using several techniques separately (Borràs *et al.*, 2015; Li *et al.*, 2019). Data fusion can be done in three levels (Figure 2) (Biancolillo *et al.*, 2014):

(1) *Low-level: a single matrix is created that includes all the raw data of the analyzed sources, as long as the data of the sensors are proportional (same row and column number), being observations of similar physical quantities (Banerjee *et al.*, 2016; Di Rosa *et al.*, 2017).*

(2) *mid-level: the data obtained from each sensor are analyzed separately and relevant characteristics are extracted from each information block. Then, the information is joined in a single matrix to perform the multivariate analysis (Borràs *et al.*, 2015).*

(3) *high-level: the information is analyzed separately and a model is generated for each block of data, and then, the responses are combined for a final fused response (Doeswijk *et al.*, 2011). Perhaps the majority vote method is the easiest and most widely used in food analysis (Di Rosa *et al.*, 2017).*

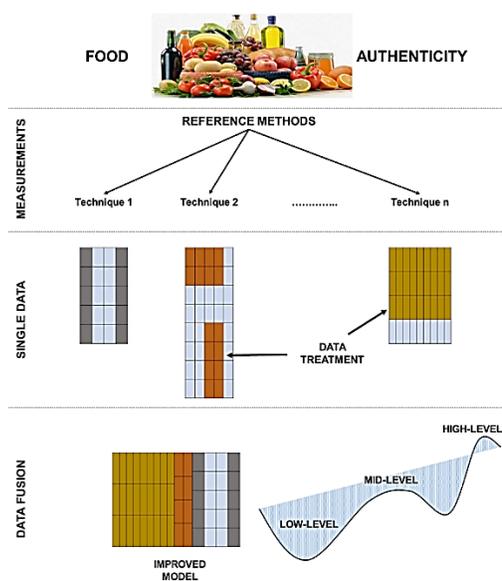


Figure 2. Data fusion approach for detecting food fraud.

Data fusion has extended in various areas such as intelligence system design (Hong *et al.*, 2003), image processing (Zhu and Basir, 2006) and food analysis (included authentication) (Ballabio *et al.*, 2018;

Sanaeifar *et al.*, 2018). Initially, the data fusion strategy was based on two data blocks (i.e. spectral and textural data obtained from hyperspectral imaging) (Xiong *et al.*, 2015), but now, the literature reports researches based on fusion data using three (Borràs *et al.*, 2016; Di Rosa *et al.*, 2017), four (Erich *et al.*, 2015) and even five techniques (Biancolillo *et al.*, 2014). In this section we summarized and described the researches based on fusion data strategy for food authentication using NIR or HIS combined with other analytic techniques.

Low-level data fusion showed good performance for classify black, green, white, yellow, dark, and oolong teas (Dankowska and Kowalewski, 2019). For this purpose, UV-Vis, synchronous fluorescence and NIR spectroscopies (individually and fused) were combined with Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Regularized Discriminant Analysis (RDA) and Support Vector Machine (SVM). Data fusion model based on NIR and UV-Vis in tandem with SVM presented the lowest classification error (<1.4%) of tea samples. However, it must be considered that low-level data fusion requires a greater amount (time) calculation, and may not compensate the non-essential variance obtained by adding the same blocks (Sun *et al.*, 2017). On the other hand, data fusion based on FT-Raman and NIR spectral (middle- and high-level) in tandem with Soft Independent Modelling of Class Analogy (SIMCA) were used for classify hazelnut paste adulterated with almond (Márquez *et al.*, 2016). Individually, FT-Raman and NIR showed sensitivity and specificity values between 75 – 100%. While, the data fusion in mid-level and high-level showed best performances for sensitivity and specificity: 96 – 100% and 88 – 100%, respectively. Mid-level data fusion based on NIR data combined with high-resolution mass spectrometry also obtained good performance to classify sulfur-fumigated Chinese herb using (Dai *et al.*, 2018). Similar results (100% correct classification in test samples) were found using mid-level data fusion based on NIR and MIR spectral data for identification of rhubarb (Sun *et al.*, 2017). The mid-level data fusion is more efficient than low-level data fusion, since by previously selecting the relevant variables of each sensor, the calculation time is reduced.

Forina *et al.* (2015) used data fusion strategy to combine artificial nose, NIR and UV-visible spectroscopy for authentication

of the PDO Chianti Classico olive oil. Individually, NIR spectral data (pre-treated by 1st derivate) presented the best performance with 100% for sensitivity and specificity. Great results were achieved (only 3 false positives) using data fusion combining 5 variables (3 NIR + 1 UV-visible + 1 artificial nose) selected by Stepwise-Linear Discriminant Analysis (STEP-LDA). In this specific case, NIR spectral data is enough to classify correctly PDO Chianti Classico olive oil. Later, NIR and mid infrared (MIR) spectroscopy were combined using data fusion (low-, mid- and high-level) for the quantification of rapeseed oil in olive oil blends (Li *et al.*, 2019). PLS regression models were constructed using the three conceptions (low-, mid- and high-level) and using the spectral data of each technique separately. The lowest RMSEP (2.86) and highest R²p (0.988) was obtained for high-level data fusion strategy, being the most reliable technique for quantitative analysis. Similar results (accuracy 99% in test samples) were found using high-level data fusion based on Raman + NIR + Proton Transfer Reaction – Time of Flight – Mass Spectrometry (PTR-MS) in tandem with PLS-DA for identify and classify 8 Italian honey botanical varieties (Ballabio *et al.*, 2018). One of the advantages of using high-level data fusion is its flexibility, since classification models do not need to be constructed using the same set of samples (Callao and Ruisánchez, 2018).

Hyperspectral images have the advantage of providing spectral and spatial information, so the fusion of data consists of obtaining characteristics of the image (i.e. texture) and combining it with the spectral data. Vis-NIR-HIS is also able to differentiate between frozen and frozen-thawed meat samples. Simultaneously, two investigations showed the ability of Vis-NIR-HIS to classify between fresh and frozen-thawed pork *Longissimus Dorsi* muscles by combining spectral information and textural features (Table 3). Pu *et al.* (2015) used six features wavelengths (400, 446, 477, 516, 592 and 686 nm) and textural features obtained by histogram statistics (HS), gray level co-occurrence matrix (GLCM) and gray level-gradient co-occurrence matrix (GLGCM). The selected wavelengths and textural features obtained by GLGCM were integrated for in a probabilistic neural network (PNN) model (classification rate = 90.91 - 93.14%). For its part, Ma *et al.* (2015) used eight important wavelengths (624, 673, 460, 588, 583, 448, 552 and 609 nm) and 45 textural features obtained by

GLGCM to obtain the best correct classification (97.73%) based on PLS-DA. On the other hand, gray level-gradient co-occurrence matrix (GLGCM) selected 35 textural features, later they were fusion with HIS spectral data to differentiate successfully (93.3% correct classification) between free-range and broiler chicken meats (Xiong *et al.*, 2015). These studies suggest that the fusion of spectral information and textural characteristics of hyperspectral images can improve the discrimination capacity of classification models.

4. Chemometrics in food authentication

Chemometrics methods are an analytical strategy to analyze the spectral information and generate mathematical models to address the problems related to food fraud (Callao and Ruisánchez, 2018). NIR and HSI provide a large amount of complex information, which often cannot be used in its gross form to generate discriminant / regression models (Pasquini, 2018). In addition, spectroscopic devices can generate information with defects such as noise, edge effect, light scattering and base line shift (Amigo *et al.*, 2015). First, spectral data should be corrected for improve model performance. The most used espectral pre-processes are: (1) multiplicative scatter correction (MSC) and (2) standard normal variate (SNV) for reducing the spectral variability caused by scattering effects (Rinnan *et al.*, 2009), and (3) Norris-Williams (NW) derivatives and Savitzky-Golay polynomial derivative filters for smoothing spectra, removing variations in baseline and resolution of overlapping peaks is used Norris-Williams (NW) derivatives and Savitzky-Golay polynomial derivative filters (Brown *et al.*, 2000). This pre-processing spectral tools were successfully applied for treating NIR and HSI spectral data in order to generate discriminant/regression models for food authentication. However, care must be taken with the application of pre-process algorithms, since vital information can be compromised. Therefore, it is important that the analyst knows the conditions of the sample and can determine if the pre-process has not compromised the analysis. In addition, some works show, erroneously, combinations of pre-process algorithms that were designed to correct the same spectral defect (as SNV and MSC). This places multidisciplinary research as an essential pillar that allows us to omit basic errors due to lack of knowledge of a specific technique.

Previous discriminant/regression model established, exploratory analysis is commonly performed. Among the unsupervised analyzes, principal component analysis (PCA) has been the most used for analysis of spectral data NIR or HSI for food authentication purposes (See Tables 1 – 5). PCA is a technique that reduces information by creating some new variables called principal components (PC) from a linear combination of the original variables (Borràs *et al.*, 2015). PCA allows to observe if the spectral characteristics allow the grouping or separation into groups of samples with specific characteristics defined previously (i.e. geographical origin). If there are no differences between the groups of samples analyzed, it should be considered to reassess the objectives of the work or verify the information referring to the response variable with which the model is being fed.

After, discriminant models or regression model are established to identify food fraud. There is a great diversity of discriminant and regression methods that allow generating mathematical models to detect fraud. A classification or prediction algorithm is not exclusive to a group of data or to a specific case of fraud.

In several cases, research on food authentication are driving to build only classification models. The main classification supervised techniques are: partial least squares discriminant analysis (PLS-DA), linear discriminant analysis (LDA) (Vandeginste *et al.*, 1998) and quadratic discriminant analysis (QDA); k nearest neighbours (KNN) (Callao and Ruisánchez, 2018), soft independent modelling of class analogy (SIMCA) (Moseholm, 1988), support vector machines (SVM) (Sliwinska *et al.*, 2014), random forest (Xu *et al.*, 2017) and artificial neural networks (Mu *et al.*, 2016). These models are used to establish specific classes based on the similarities and differences of the samples analyzed. Then, an external sample can be classified or not in a certain class. The choice of classifier happens not only for having a high precision, but also for reducing the computational time of analysis. Many of the models studied in this review have been created using the full spectrum. However, it is necessary that new studies be directed to evaluate methods of selection of variables in order to establish more precise models.

Between regression algorithms, partial least square (PLS) is the most popular supervised techniques used to build regression models based on spectral data

for food identification (see Table 1 – 5). PLS goal is to analyze or predict a set of dependent variables from a set of predictors (independent variable) which are rotated to ensure maximum correlation efficiency (Alamprese et al., 2013). Therefore, PLS generates a mathematical model that correlates linearly the spectral variables with the variable of interest (i.e. adulterant concentration) (Alamprese et al., 2016). These linear combinations are called latent variables, and they have a great predictive capacity, especially the first latent variables (Kumar and Chandrakant-Karne, 2017). It is important, especially for HSI applications, that PLS models be constructed using only significant wavelengths.

5. Future trends

This review summarizes and analyzes the latest advances in the use of NIR and HSI for food authentication. In the case of NIR, although it seems to be a fairly mature technique (Pasquini, 2018), it can still be explored for new foods and new forms of fraud. For its part, HSI is a technique still in exploration for food authentication purposes. Although HSI can have the advantage of incorporating spatial information, processing that information is very tiring, time consuming and impractical for industrial applications. Future works based on HSI, but also on NIR, must generate multispectral models that allow the technology to be explored at an industrial level. Multispectral models are constructed with the appropriate selection of variables, therefore, new methods in the selection of variables should be explored.

On the other hand, although the developed models based on NIR and HSI may have outstanding results, they may not be conclusive. Some limitations in the applications of both techniques have been overcome using data fusion. The fusion of data, at a certain level, allows to obtain more robust and precise models. Perhaps an important challenge in the next works is to establish new ways to merge groups of data to obtain more precise results.

Regarding the manageability of NIR and HSI devices. It is expected that in the not too distant future, smaller portable devices will be available. These devices must be manageable, cheap, robust and easy to apply (Croccombe, 2018). The loss of precision in portable devices is a topic to be addressed by the scientific community. Therefore, it is necessary to publish more research using portable devices, considering the influence of temperature and the movement of the sample in on-line

system. Thinking about the final consumer, the NIR and HSI devices must be implemented in smartphone (Kartakoullis et al., 2019), with a friendly language and an interface that is easy to apply. In addition, devices should respond to different food groups. For this, it is important to build these equipment using important wavelengths for faster and more accurate analysis.

6. Conclusions

The application of NIR and HSI for food authentication has gained more interest in recent years. Both techniques require a minimum or no sample preparation, are non-invasive, do not use reagents ("green analytical method") and are quite reliable. The spectral information of NIR and HSI combined with chemometrics are generally sufficient to create mathematical models to identify geographic origin, farming system, genetic variety and adulterated samples. The ease of obtaining NIR data allows it to be the technique with the greatest industrial proximity. Although there are still challenges for its implementation in large-scale production lines. For its part, HSI can overcome the limitations of the heterogeneity of the sample and for certain cases obtain a greater amount of valuable information to detect food fraud. Most papers report models based on HSI information using the full spectrum. What would not be industrially viable, therefore, multispectral models are usually a very useful solution. When both techniques, NIR and HSI, do not reach the expected results individually, the data fusion strategy is shown as a promising alternative. The portability of the equipment and the remote access via Wi-Fi or Bluetooth will allow fraud control to be carried out throughout the production chain. In addition, network connections will allow NIR and HSI devices to record information on the network, becoming part of the "Internet of things". Finally, the studies registered in this review are mostly laboratory-level applications, therefore, it is very likely that with the continuous development of technology, more manageable and precise NIR and HSI devices allow industrial studies.

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