

# A Review of the Principles and Applications of Near-Infrared Spectroscopy to Characterize Meat, Fat, and Meat Products

Nuria Prieto<sup>1</sup>, Olga Pawluczuk<sup>2</sup>, Michael Edward Russell Dugan<sup>1</sup>,  
and Jennifer Lynn Aalhus<sup>1</sup>

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## Abstract

Consumer demand for quality and healthfulness has led to a higher need for quality assurance in meat production. This requirement has increased interest in near-infrared (NIR) spectroscopy due to the ability for rapid, environmentally friendly, and noninvasive prediction of meat quality or authentication of added-value meat products. This review includes the principles of NIR spectroscopy, pre-processing methods, and multivariate analyses used for quantitative and qualitative purposes in the meat sector. Recent advances in portable NIR spectrometers that enable new online applications in the meat industry are shown and their performance evaluated. Discrepancies between published studies and potential sources of variability are discussed, and further research is encouraged to face the challenges of using NIRS technology in commercial applications, so that its full potential can be achieved.

## Keywords

Near-infrared spectroscopy, portable instruments, online, meat, fat, quality

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## Introduction

When consumers purchase meat, price and quality are important to their decisions; however, an increasing number of consumers also factor in health implications of meat consumption when making a purchase.<sup>1,2</sup> This demand for quality and healthfulness has led to a higher need for quality assurance in meat production. To meet this demand, new objective quality control methods are required as traditional means of analysis are lengthy, require toxic solvents and reagents, and can have high costs. For these reasons, the development of rapid, environmentally friendly, and noninvasive methods for either prediction of meat quality or authentication of added-value meat products has become a priority in the last years. In this regard, near-infrared (NIR) spectroscopy could be considered as a rapid and cost-effective alternative.

Although NIR spectroscopy is referred to as a new technology, it was discovered in 1800 when Herschel found that dispersion of electromagnetic waves beyond the visible range of the spectrum could be observed by using a series of thermometers with blackened bulbs.<sup>3</sup> However, it was not until the 1960s when major developments occurred with NIR spectroscopy technology, allowing its application in various aspects of animal production.<sup>4</sup> For

meat, NIR spectroscopy was not used for on-/inline purposes until 1996, when Isaksson et al.<sup>5</sup> used a conveyor NIR instrument located at the outlet of the meat grinder to predict the fat, moisture, and protein content of ground beef.

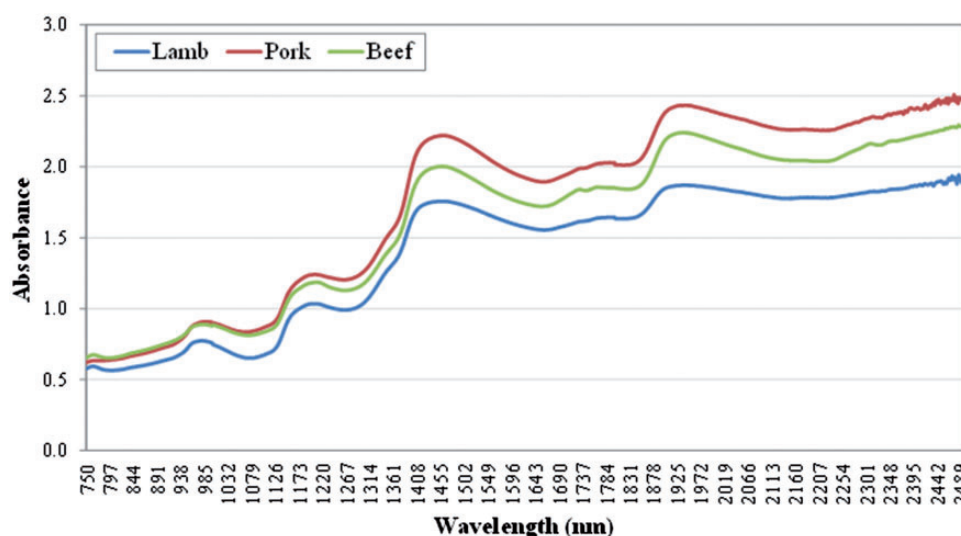
Near-infrared spectroscopy measures the absorption of electromagnetic radiation including wavelengths from 750 to 2500 nm. The NIR spectra include broad bands that arise from absorptions in overlapping wavelengths. The absorptions measured by NIR spectroscopy correspond mostly to overtones and combinations of vibrational modes involving C–H, O–H, and N–H chemical bonds.<sup>6</sup> Recording the electromagnetic radiation absorbed from those molecular bonds in the NIR wavelengths produces spectra which are unique to a sample acting as a “fingerprint”. The collected spectrum includes data related to the chemical and physical

<sup>1</sup>Lacombe Research and Development Centre, Agriculture and Agri-Food Canada, AB, Canada

<sup>2</sup>P&P Optica Inc, Kitchener, ON, Canada

## Corresponding author:

Nuria Prieto, Lacombe Research and Development Centre, 6000 C&E Trail, Lacombe, Alberta, T4L 1W1, Canada.  
Email: nuria.prietobenavides@agr.gc.ca



**Figure 1.** Near-infrared spectra collected with a portable instrument on intact meat samples from several species. Source: Agriculture and Agri-Food Canada–Lacombe.

properties of organic molecules in the sample and, therefore, important information on sample composition. Examples of NIR spectra collected on intact meat from several species using a portable instrument are presented in Figure 1.

Recently, efforts have focused on applying this technology to meat analyses. Several comprehensive reviews<sup>7–9</sup> have summarized studies reporting the capabilities of NIR spectroscopy in the area of meat quality. However, this technology still has some limitations and online applications under industrial environments remain challenging.

This review provides a summary of recent uses of NIR spectroscopy in the meat sector, emphasizing papers published after 2010. Discrepancies between published studies and potential sources of variability are discussed, and further research is encouraged to face the challenges of using this technology in commercial field applications, so that its full potential can be achieved.

## Fundamentals of Near-Infrared Spectroscopy

The NIR spectrometers include a light source, beam splitter system (wavelength selector), sample detector, optical detector, and data processing/analyzing system. These parts can have different properties and should be selected based on their intended use to provide an effective and consistent instrument. The most commonly used NIR radiation sources are quartz–tungsten–halogen (QTH) lamps; this is due to the low cost and high intensity radiation in the NIR wavelengths where the spectral output is continuous. However, QTH lamps present several problems in industrial application due to their low energy efficiency, heat generation, temperature sensitivity, vibration sensitivity,

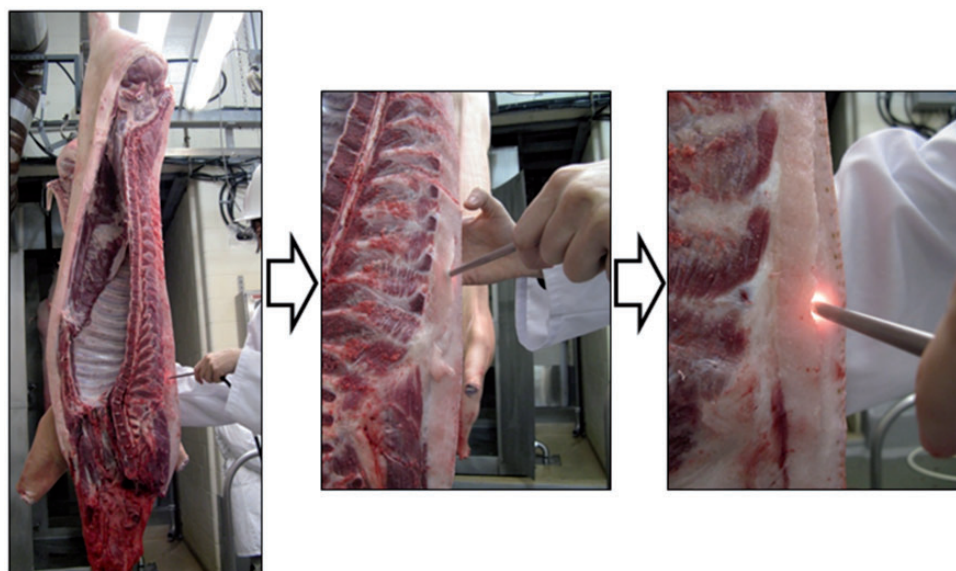
and long start-up times. In contrast, light emitting diodes (LED) have recently emerged in the NIR field as they address several of the problems with QTH light sources. Due to the higher efficiency of LED illumination systems, power requirements are lower for the same brightness. Furthermore, excess heat production is not an issue with LED illumination sources. However, due to the costliness of LED, they have not been widely adopted in NIR spectrometers.<sup>10</sup> Beam splitter systems in NIR spectrometers output single-color light translated from multi-color input. These systems use light filters in discrete-wavelength spectrophotometers, or interferometer and gratings in continuous spectrum NIR instruments.

When spectra are collected, NIR radiation interacts with the sample and the energy may be absorbed, transmitted, or reflected. As such, various modes of measurements can be applied in NIR spectroscopy designed to suit different uses. These measurement modes include: transmittance, interactance, transreflectance, diffuse transmittance, and diffuse reflectance, with the latter two methods being applied most often.<sup>11</sup> The choice of measurement is dependent on sample characteristics; for example, the phase (i.e., solid or liquid), translucency, and by the size of the particles.

Sample detectors within the NIR spectrometer differ by spectral response, speed of response, and the minimum threshold for detectable radiant power. Most commonly, NIR spectrometers utilize single and multi-channel photon detectors. Single-channel detectors use lead salt semiconductors such as lead sulfide (PbS, 1100–2500 nm), indium gallium arsenide (InGaAs, 800–1700 nm or extended range up to 2500 nm), and silicon detectors (400–1100 nm). Multi-channel detectors utilize diode arrays or charge-coupled devices (CCDs).<sup>12</sup> The use of



**Figure 2.** Real-time collection of NIR spectra at the rib-eye from beef using a portable instrument. Source: Agriculture and Agri-Food Canada–Lacombe.



**Figure 3.** Real-time collection of NIR spectra from the inner layer of pig subcutaneous fat using a portable instrument.<sup>70</sup>

the different sample detectors varies according to sample properties: liquid samples are often analyzed in glass or quartz chambers of different sizes, while diffuse reflection carrier accessories are generally used for solid samples. Many sample detectors or chambers are constrained for use in laboratory settings; however, recently developed portable handheld devices are more compact, have simplified use, designs that are more robust, and lower cost. These developments enable use of NIR spectroscopy technology in a greater variety of applications. In this regard, the

fiber optic cable in portable instruments is now being used for online application to evaluate the quality of meat, fat, and meat products (Figures 2 and 3). Several of these portable NIR spectrometers are now available for purchase and vary in cost and designated application. See dos Santos et al.<sup>8</sup> for an excellent review of the different specifications for portable NIR instruments most often used in scientific research and potential applications in the agri-food sector.

In the last few years, NIR spectrometers using micro-electro-mechanical systems (MEMS) technology have been



**Figure 4.** Fully packaged micro-electro-mechanical systems (MEMS)-based NIR spectrometer, approximate size is 6 in  $\times$  4 in  $\times$  1 in ( $\sim$ 15.3 cm  $\times$  10.2 cm  $\times$  2.5 cm).<sup>14</sup>

developed. The combination of MEMS with mathematic transformations, such as digital transform spectroscopy (DTS), produces powerful spectrometers with several clear advantages. The MEMS chips equipped with fixed diffraction grating are rapidly programmable and the use of a high-contrast pixilated optical reflector working as a tunable spectral filter, combined with a single detector, can reduce equipment costs while eliminating detector noise. The MEMS-based NIR spectrometers are also particularly useful in in situ applications due to the reduction in moving parts and robustness in design.<sup>13</sup> These design advantages and the high-resolution collection allow the use of MEMS-based NIR spectrometers in environments with high levels of vibration and variable temperatures where other designs might not be suitable. Therefore, MEMS technology represents a paradigm shift for industrial applications of NIR spectroscopy, introducing new opportunities for spectroscopic sensors (Figure 4).<sup>14</sup> For instance, Pügner et al.<sup>15</sup> have recently developed a novel hybrid-integrated MEMS scanning grating spectrometer to estimate chemical components in food products with low power consumption (a few milliwatts) and a volume of only 2.1 cm<sup>3</sup>, which could potentially be implemented in smartphones.

Advances in computing power and statistical programs have allowed NIR spectroscopy to output data almost in real time. However, the raw spectra collected from NIR spectrometers contain background data and noise besides the sample data. The absorption signals are often relatively weak compared with interference in the interaction between light and particles. Interferences that introduce noise in collected spectra can include: water absorption bands, scattering effects, instrumental noise, sample complexity, extraneous light sources, and matrix/environmental effects. Additionally, distinct chemical molecules can present absorption peaks that overlap in several regions along spectra. As such, mathematical pre-processing of spectral data is required in order to obtain valuable

information about chemical properties from samples; this processing is referred to as chemometrics. Chemometric methods have been described in detail in previous literature<sup>16</sup> and it is not the aim of this review to cover chemometric details; however, a brief summary is provided here. Smoothing is used to reduce instrumental noise or background information and de-trending techniques are usually performed to reduce the effects of accumulating data sets from a trend. Derivatives are commonly used to reduce insignificant baseline signals from samples.<sup>17</sup> Pre-processing methods that involve normalizations, such as multiple scatter correction (MSC) and standard normal variate (SNV), have been used to correct path length effects, scattering effects, source or detector variations, and some instrumental sensitivity effects.<sup>18</sup> More recently, orthogonal signal correction (OSC), direct orthogonal signal correction (DOSC), and orthogonal wavelet correction (OWAVEC) have been developed to reduce light-scattering effects, among other types of interference.<sup>19</sup> Net analyte signal (NAS) is comparable to OSC insofar as both algorithms are orthogonal to concentration matrix with spectral matrix. However, NAS has attracted more attention in chemometrics, as it can also be used in additional multivariate calibrations, such as sensitivity, selectivity, signal-to-noise ratio, and limit of detection for the spectral figures.<sup>20</sup> Wavelet transforms (WT) has become a popular pre-processing method today due to the rapid compression of data sets in order to remove the noise and background signals.<sup>21</sup>

Following mathematical pre-processing, a prediction model must be built, referred to as the calibration. The calibration is a regression model allowing prediction of chemical properties based on spectral data. Usually, NIR spectra do not have specific wavelengths that directly correlate with distinct sample properties; this is due to overlapping bands in the spectra resulting from various chemical and physical attributes of complex samples. As such, using a least squares regression (LSR) based univariate calibration is ineffective, as a direct relationship of the property to be predicted and the measured signal is required. Therefore, a multivariate calibration is needed; this is accomplished by using the data from all or some wavelengths as spectral predictor variables. Numerous multivariate approaches have been used for building reliable calibration models for quantitative analysis in food. Early calibration methods from the 1960s and 1970s were conducted using multiple linear regression (SMLR),<sup>12</sup> using a discrete number of wavelengths from filter instruments. However, spectral measurements have high linear relations between variables, resulting in an issue called multicollinearity. With the emergence of computer science in the 1980s and the introduction of monochromators to record full range spectra, more sophisticated approaches to solve the multicollinearity problem were developed. These consist in developing orthogonal (uncorrelated) linear combinations from



spectral variables (components or factors) instead of using the original data to establish regression equations. Algorithms such as principal component regression (PCR) or partial least squares regression (PLSR) provide more stable and reliable regression equations and predictions,<sup>12</sup> since the variables are compressed through removal of unrelated and unstable data, such as noise and redundancy, while retaining most of the meaningful information. Principal component regression is conducted by using principal component analysis (PCA) of the spectral variables for data compression, and subsequently LSR between selected principal components (PC) and the reference values. Partial least squares regression differs from PCR by using the information of both spectroscopic and parameter variables analyzed in samples. Nevertheless, increases in calibration database size have highlighted the need for analyzing nonlinear relationships using calibration methods. To overcome intrinsic nonlinearities within data sets, nonlinear regression approaches such as local regression methods (e.g., locally weighted regression [LWR]) or artificial neural networks (ANN) have been recently applied.

Qualitative analyses can also be applied to NIR spectral data. Qualitative methods are referred to as pattern recognition methods in which individual samples categorized prior to analysis are classified based on collected spectra. Several methods can be used for qualitative analyses including: ANN, cluster analysis (CA), discriminant partial least square (DPLS), K-nearest neighbors (KNN), linear discriminant analysis (LDA), PCA, soft independent modeling of class anthology (SIMCA), and support vector machine (SVM). A comprehensive review of qualitative methods as well as their applications can be found in Cen and He.<sup>10</sup>

Once the calibration has been performed, a validation process is required to ensure successful calibration models. The validation method commonly used is the internal or cross-validation, where the same data set used for calibration is used in the validation. However, external validations using a separate and independent sample set (test set) provide more reliable and relevant estimates of the future prediction ability of the model.<sup>9</sup> Hence, it becomes very important to select a representative set of samples providing the largest information for the calibration data set, since it is of critical importance that this data set represents as much variation as possible that will be encountered in future samples. Despite the external validation being the most desirable option, its application may not be always possible; especially in research studies where biological samples are involved and the number of animals available per experiment is limited.

Developing an adequate calibration data set can be difficult and expensive, as such calibrations are thought to be a major challenge with NIR spectroscopy. Hence, sharing of model libraries and transferring multivariate calibration models is important in order to provide large databases with, likely, a higher variability. Nevertheless, the transfer

of the calibration models may not always be compatible between instruments; therefore, this possibility is suitable only when the same spectral data sets can be used in different environments and instruments. Methods for transferring calibration models to make the spectra less dependent of instrumentation variation can be found in the review of Cen and He.<sup>10</sup> Zamora-Rojas et al.<sup>22</sup> demonstrated the successful transfer of calibration models, where large calibration data sets collected previously were used with new NIR spectroscopy devices better suited to in situ analysis. Nevertheless, despite possibilities for several methods of calibration transfer, there is always a loss of precision when compared to the original models.

Calibration models are usually assessed for their predictive ability using coefficient of determination ( $R^2$ ), root mean square error of cross-validation (RMSECV), or prediction (RMSEP) depending on the type of validation undertaken,<sup>23</sup> and ratio of performance deviation (RPD).<sup>24,25</sup> The equations for root mean square error (RMSE) and RPD are defined in Eqs. 1 and 2:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (1)$$

$$RPD = \frac{SD}{RMSE} \quad (2)$$

where  $n$  is the number of samples in the calibration set,  $y_i$  represents the measured responses,  $\hat{y}_i$  is the estimated responses obtained through cross-validation or external validation, and SD corresponds to the standard deviation of reference values from calibration or prediction set.

Since its first introduction in a peer-reviewed publication in 1993,<sup>26</sup> RPD is gradually becoming widely used for quick assessment of an NIR spectroscopy calibration model due to its non-dimensionality. The calculated RMSE should be considerably less than the SD and ideally the RPD should be 5 or higher.<sup>27</sup> Low RPD values may in part be due to a low variability in reference values or a large RMSE relative to SD.<sup>28</sup> Values of over 20 have been observed for the prediction of some factors, such as moisture content of whole-kernel corn (maize). However, due to complications caused by sample preparation, sample presentation, difficulties with reference testing, and characteristically low variability in a sample set, RPD values of  $\geq 3.0$  may be difficult to obtain. In these circumstances the NIR spectroscopy may still have value for use as an analytical tool in both scientific and industrial contexts. Table 1<sup>27</sup> provides RPD ranges which correspond to appropriate application of NIR spectroscopy for samples which have more complex physical structures, and in prediction of more functional attributes such as meat texture, where no "classical" absorbers are directly associated with them.

**Table 1.** Degrees of merit for the ratio of performance deviation (RPD) to the application of NIR spectroscopy.<sup>27</sup>

RPD value	Classification	Application
0.0–1.9	Very poor	Not recommended
2.0–2.4	Poor	Rough screening
2.5–2.9	Fair	Screening
3.0–3.4	Good	Quality control
3.5–4.0	Very good	Process control
4.1+	Excellent	Any application

## Application of Near-Infrared Spectroscopy to Characterize Meat Fat and Meat Products

### Prediction of Chemical Components

Evaluation of meat composition is essential due to its relationship with overall quality and palatability characteristics, wholesomeness, and impact on consumer health. Many studies exploring NIR spectroscopy application for the analysis of chemical composition of meat have been reported over the past few years and a selection of studies (Table 2) are discussed below for individual meat chemical components.

The ability to predict protein, fat, and moisture content in meat samples using NIR spectroscopy has been covered in previous reviews.<sup>7,29</sup> Nevertheless, even today, variable results are found in different studies. Liao et al.<sup>30</sup> used a conveyor spectrometer to scan (350–1100 nm) intact slices of *M. longissimus dorsi* under simulated online conditions and found a great variability in the results depending on the method used for spectra pre-processing. These authors observed that the multiplicative scatter correction (MSC) in conjunction with a first derivative provided the most accurate calibration models. These pre-processing procedures eliminated the negative impact of the translational error independent of wavelength in the reflectance spectra. Such errors are caused by varying sample thicknesses that can greatly affect the calibration procedure. Nevertheless, despite the mathematical treatment applied to the spectra, visible–near-infrared (Vis-NIR) spectroscopy was suitable only for rough screening purposes for moisture content and unsatisfactory for protein and intramuscular fat content predictions, according to the criteria established by Williams.<sup>24,25</sup> These results could have been due to the small range of values for protein content and the lack of homogeneity in intact meat.<sup>30</sup> Thus, these authors indicated that predictability of Vis-NIR spectroscopy could be improved by increasing sample numbers and the variability of muscles. Additionally, predictions could be improved by utilizing NIR spectral data from wavelengths above 1100 nm; this region contains spectral data important for the prediction of chemical components.<sup>29</sup> Due to the lack of homogeneity, repetitive scans were not totally replicated

in a single sample; increasing the scans per sample or using a larger surface area for each scan could also help to improve precision. These results agree with Prieto et al.<sup>31</sup> and Balage et al.,<sup>32</sup> who reported low NIR spectroscopy predictability for intramuscular fat content in beef and pork, respectively, when spectra were collected on intact muscle using fiber optic devices from 350–1800 nm and 400–1395 nm, respectively.

In order to overcome the lack of homogeneity and the limited spectral range, Prieto et al.<sup>33</sup> tested NIR spectroscopy potential to predict chemical composition in beef where the spectra were collected (400–2498 nm) with benchtop equipment on homogenized meat samples. Despite using homogenized samples, NIR spectroscopy was only suitable for rough screening purposes for the moisture, protein, and intramuscular fat content, probably due to the limited number of cattle used in the study (i.e., only 63 steers were used and fed diets containing either sunflower or flaxseed in order to modify meat fatty acid (FA) profiles). Prevornik et al.<sup>34</sup> tested NIR spectroscopy (400–2500 nm) on homogenized samples to predict chemical composition in a diverse set of raw meats and meat products including several pork muscles and muscles obtained from different species. These authors demonstrated the remarkable ability of NIR spectroscopy to predict moisture, protein, and intramuscular fat content over the diverse sample set. However, unreliable predictability was observed for moisture and protein content when only the pig longissimus dorsi muscle was considered. These results showed again the importance of a wide range of variability of the components to enable their accurate prediction by NIR spectroscopy. Indeed, when Su et al.<sup>35</sup> tested NIR spectroscopy (1000–1800 nm) to predict the main chemical components in homogenized beef samples with a wide range of variability, NIR spectroscopy was reported to have an outstanding ability to predict moisture, protein, and intramuscular fat content.

Hence, the results from the previous studies show that NIR spectroscopy has potential to replace existing wet chemistry methods to successfully estimate meat chemical composition. Nevertheless, in order to obtain prediction equations accurate enough to be used in quality and process control, both a wide range of chemical composition variability and sample homogenization are required. These constraints can hamper the implementation of NIR spectroscopy online, where further improvement is still necessary before industrial use can be considered.

Meat is a major contributor of lipids to the human diet. Consumers have become more interested in the fat composition of meat due to nutritional guideline recommendations for reducing total fat and saturated fatty acids (SFA) intake, while increasing consumption of polyunsaturated fatty acids (PUFA).<sup>36</sup> Hence, there is a growing demand for fast and efficient alternative methods to monitor meat FA profiles. In this regard, several studies have tested the

**Table 2.** Summary of applications of NIR spectroscopy to predict chemical components in meat (sorted by species and publication year).

Species	Sample presentation	Attributes	Spectrometer, spectral range (nm) Acquisition mode	Multivariate analysis	Calibration and prediction performance				Reference
					R <sup>2</sup> <sub>CAL</sub>	SECV	RPD		
Pig	Intact	IMF (g/kg)	EPP2000 400–1395 Reflectance	PLSR	0.28	1.03 <sup>†</sup>	1.3		Balage et al. (2015) <sup>32</sup>
Pig	Intact	Moisture (%)	USB4000	PLSR	0.42–0.83	0.78–1.34	1.16–2.01		Liao et al. (2010) <sup>30</sup>
		Protein (%)	350–1100 Reflectance		0.07–0.82	0.40–0.74	1.01–1.74		
		IMF (%)			0.16–0.85	0.08–0.15	1.03–1.77		
	Ground	SFA (mg/g meat)	NIRSystems6500	MPLSR	0.93*	108.8	3.82		Mourot et al. (2015) <sup>44</sup>
Beef	Ground	MUFA (mg/g meat)	400–2500 Reflectance	PLSR	0.93*	116.0	3.68		
		PUFA (mg/g meat)			0.59*	28.71	1.54		
		CLA (mg/g meat)			0.79*	2.38	2.14		
		Omega-3 (mg/g meat)			0.37*	8.32	1.25		
		Omega-6 (mg/100 g meat)			0.58*	22.09	1.52		
		Moisture (%)	NIRSystems6500		0.90	0.60	2.13		Prieto et al. (2014) <sup>33</sup>
		Protein (%)	400–2498 Reflectance		0.85	0.48	2.10		
		IMF (%)			0.86	1.08	2.01		
		SFA (mg/g meat)			0.97	1.05	4.54		
		MUFA (mg/g meat)			0.96	1.15	4.11		
Beef	Ground	PUFA (mg/g meat)		PLSR	0.44	0.21	1.18		Su et al. (2014) <sup>35</sup>
		CLA (mg/g meat)			0.83	0.04	2.28		
		Omega-3 (mg/g meat)			0.61	0.12	1.36		
		Moisture (%)	SupNIR-1500		0.92–0.997	1.22–4.95	2.63–10.69		
		Protein (%)	1000–1800 Reflectance		0.92–0.99	0.70–1.41	2.71–5.46		
Beef	Intact (AA×/LIMx)	IMF (%)		PLSR	0.998–0.998	0.99–1.20	14.22–17.37		Prieto et al. (2011) <sup>31</sup>
		IMF (mg/100 g meat)	LabSpec2500		0.43/0.75	1029/477	1.1/1.9		
		SFA (mg/100 g meat)	350–1800 Reflectance		0.40/0.68	405/235	1.1/1.7		
		MUFA (mg/100 g meat)			0.44/0.75	452/240	1.1/1.9		
		PUFA (mg/100 g meat)			0.16/0.64	16/17	1.0/1.5		
		Omega-3 (mg/100 g meat)			0.43/0.12	8.1/9.0	1.1/1.0		
		Omega-6 (mg/100 g meat)			0.73/0.45	18/21	1.4/1.1		
		IMF (%)	FieldSpec 350–2500 Reflectance	GA-PLSR	0.71*	1.60 <sup>†</sup>	1.77		
Lamb	Intact	SFA (mg/100 g meat)		GA-PLSR	0.61*	192.21 <sup>†</sup>	1.61		Pullanagari et al. (2015) <sup>39</sup>
		MUFA (mg/100 g meat)			0.62*	168.72 <sup>†</sup>	1.56		
		PUFA (mg/100 g meat)			0.71*	27.86 <sup>†</sup>	2.11		

(continued)

Table 2. Continued

Species	Sample presentation	Attributes	Spectrometer, spectral range (nm) Acquisition mode	Multivariate analysis	Calibration and prediction performance			
					R <sup>2</sup> <sub>CAL</sub>	SECV	RPD	Reference
Lamb	Intact/Ground	SFA (g/100 g meat)	NIRSystems6500 400–2500 Reflectance	MPLSR	0.52/0.98*	0.55/0.13	1.43/6.78	Guy et al. (2011) <sup>37</sup>
		MUFA (g/100 g meat)			0.46/0.98*	0.59/0.14	1.34/6.81	
		PUFA (g/100 g meat)			0.45/0.89*	0.08/0.04	1.32/3.00	
		CLA (g/100 g meat)			0.41/0.84*	0.02/0.01	1.32/2.46	
		Omega-3 (g/100 g meat)			0.35/0.78*	0.02/0.01	1.21/2.08	
Chicken	Intact	Omega-6 (g/100 g meat)	LabSpec2500 350–1830 Reflectance	MPLSR	0.37/0.83*	0.07/0.04	1.23/2.43	De Marchi et al. (2012) <sup>40</sup>
		SFA (% of total FA)			0.16	1.66	1.17	
		MUFA (% of total FA)			0.41	2.58	1.36	
		PUFA (% of total FA)			0.39	3.35	1.29	
		Omega-3 (% of total FA)			0.28	0.26	1.27	
Chicken	Ground (% of total FA / mg FA, 100 g <sup>−1</sup> meat)	Omega-6 (% of total FA)	FoodScan 850–1050 Transmittance	MPLSR	0.39	3.10	1.29	Riovanto et al. (2012) <sup>41</sup>
		SFA			0.09/0.92	1.51/53.6	0.66/4.86	
		MUFA			0.59/0.98	2.29/70.1	1.46/4.73	
		PUFA			0.44/0.65	3.15/62.0	1.34/2.84	
		Omega-3			0.39/0.39	0.39/5.0	1.38/1.86	
Chicken	Freeze-dried ground (% of total FA / g FA, kg <sup>−1</sup> meat, DM)	Omega-6	NIRSystems6500 400–2500 Reflectance	MPLSR	0.41/0.67	2.76/57.9	1.41/2.88	Zhou et al. (2012) <sup>42</sup>
		SFA			0.29/0.95	1.23/0.87 <sup>†</sup>	1.2/4.0	
		MUFA			0.96/0.94	3.29/1.12 <sup>†</sup>	1.6/4.2	
		PUFA			0.96/0.97	2.74/0.83 <sup>†</sup>	1.9/2.6	
		Omega-3			0.86/0.95	0.24/0.08 <sup>†</sup>	2.1/2.5	
Several species	Ground	Omega-6	NIRSystems6500 400–2500 Reflectance	PLSR	0.97/0.98	3.38/0.79 <sup>†</sup>	1.6/2.5	Prevolnik et al. (2010) <sup>34</sup>
		Moisture (%)			0.91–0.99	0.35–1.38 <sup>†</sup>	1.2–5.0	
		Protein (%)			0.10–0.93	0.39–0.88 <sup>†</sup>	1.1–4.5	
		IMF (%)			0.96–0.99	0.16–2.14 <sup>†</sup>	4.1–10.1	

\*Coefficient of determination of cross-validation.

<sup>†</sup>Standard error of prediction.AA ×, Aberdeen Angus crossbred; LIM ×, Limousin crossbred; DM, dry matter basis; IMF, intramuscular fat; SFA, saturated fatty acids; MUFA, monounsaturated fatty acids; PUFA, polyunsaturated fatty acids; CLA, conjugated linoleic acid; PLSR, partial least squares regression; MPLSR, modified partial least squares regression; GA-PLSR, genetic algorithm based partial least squares regression; R<sup>2</sup><sub>CAL</sub>, coefficient of determination of calibration; SECV, error standard of cross-validation; RPD, ratio of performance deviation.



potential of NIR spectroscopy to predict the FA composition in meat from different species (Table 2, only FA groups are shown). Guy et al.<sup>37</sup> reported NIR spectroscopy prediction models were improved by using ground versus intact non-ground muscle samples from lambs ( $R^2$  of cross-validation: 0.29 to 0.98 versus 0.05 to 0.53 for individual and groups of FA, respectively). This is likely the result of heterogeneity of intact muscle. While the ability to collect NIR spectra from intact non-ground muscle would be advantageous from a practical perspective, the heterogeneous nature of muscle probably limits the ability to generate accurate calibration models for FA contents based on NIR spectra. Additionally, the type of milling treatment has a marked effect on the quality of the FA prediction models. For instance, Guy et al.<sup>37</sup> ground and finely powdered the samples in liquid nitrogen, obtaining a very homogeneous muscle sample, and this produced much better results than those obtained on samples minced using simple commercial choppers.<sup>38</sup> Also, the liquid nitrogen treatment reduced lipolysis, peroxidation, and breakdown caused by heat generated with the grinding process. Guy et al.<sup>37</sup> also observed that the accuracy of prediction models varied with the FA content: predictions were satisfactory for FA groups or individual FA present at medium-to-high concentrations (total SFA, *cis*, and total monounsaturated FA (MUFA), 16:0, 18:0, 18:1  $\Delta^9$  *cis*), but lower for FA generally found in meat at low or very low concentrations (18:1  $\Delta^9$  *trans*, 18:2 omega (n)-6, 20:3 n-6, 20:5 n-3, 22:5 n-3, 22:6 n-3, total n-3 PUFA). As major constituents are more easily predicted by NIR spectroscopy than compounds with low concentrations, these authors suggested that increasing the presence of some minor FA through dietary treatments would improve accuracy of the prediction models. Low prediction accuracies were also observed by Pullanagari et al.<sup>39</sup> for individual and groups of FA when NIR spectra were collected on intact longissimus lumborum from lambs. Although meat heterogeneity can originate the portion of muscle scanned is not representative of total FA variation of that muscle, these authors attributed the lack of success to the large standard errors of laboratory. Hence, Pullanagari et al.<sup>39</sup> suggested that NIR spectroscopy prediction ability might be further enhanced by improving the efficiency of fat extraction for reference samples.

The effect of sample pre-processing treatment on NIR spectroscopy predictability for FA content has also been observed in chicken meat. De Marchi et al.<sup>40</sup> reported a limited ability of NIR spectroscopy to predict both individual and groups of FA on intact breasts. Besides the heterogeneity of the samples, these authors indicated that another aspect that could affect NIR spectroscopy prediction performance would be the fat content of the samples. Chicken breast muscle has a low-fat content; as such the FA profile is more difficult to estimate due to the limited ability of NIR spectroscopy to detect compounds that are contained in

the organic matter at very low concentration. Despite the above limits, De Marchi et al.<sup>40</sup> indicated that the application of an online spectroscopic analysis could be useful for improving the FA composition of meat through genetic selection programs; however, further investigation is required to confirm this application in chicken. In contrast, much higher NIR spectroscopy predictability for FA profile (expressed in absolute concentrations) was observed when spectra were collected on ground chicken breast,<sup>41</sup> with exceptional NIR spectroscopy ability to predict SFA and MUFA, and suitable for screening purposes for PUFA and n-6 FA content. Although the NIR spectroscopy predictability for individual FA is not shown in this review, these authors reported that the NIR transmission spectroscopy showed the best prediction performances for the major FA which were well represented in chicken meat (oleic, linoleic, palmitic, and stearic acids with  $R^2$  of 0.98, 0.70, 0.94, and 0.79, respectively). Some individual PUFA were the hardest to predict probably due to the low content of PUFA in chicken meat samples. Several reasons have been indicated in the literature for the lack of NIR spectroscopy success to predict PUFA. The similarities in their NIR absorption pattern due to the presence of identical functional groups could make difficult the accurate estimation of these minor components. The greater number of double bonds in PUFA result in less C-H bonds that can be detected in the NIR region, potentially contributing to lower prediction accuracy of PUFA by NIR spectroscopy.<sup>31</sup> Moreover, the main sources of PUFA in meat are phospholipids which are found in plasma and intracellular membranes, as opposed to triacylglycerols, which are found in discrete highly concentrated lipid droplets.

Riovento et al.<sup>41</sup> and Zhou et al.<sup>42</sup> also evaluated the potential of NIR spectroscopy to predict the FA profile in chicken breast with each FA expressed as a percentage of total fat. The authors from both studies observed that FA were predicted at lower levels when they were expressed as a percentage of FA compared to absolute concentration (mg FA per 100 g meat, g FA per kg meat, respectively). Correlating the NIR spectroscopy spectral data with absolute concentration of FA should be more accurate than using proportions, since NIR absorbance depends on the quantity of molecular bonds in the organic matrix.<sup>31,38</sup> Hence, Riovento et al.<sup>41</sup> and Zhou et al.<sup>42</sup> corroborated that the unit of measurement used to express reference data can influence the NIR spectroscopy prediction performance. Regarding spectra pre-processing, both studies showed that derivatives combined with certain scatter correction methods such as MSC and SNV and detrend (SNV-D) provided the best predictions and recommended that, for each FA calibration equation, the ideal mathematical pre-treatment should be identified to maximize the performances. Riovento et al.<sup>41</sup> and Zhou et al.<sup>42</sup> concluded that freeze drying process and/or milling treatment are time consuming and do not permit the application of NIR

spectroscopy as an online analytical technique, but they seem necessary to guarantee accurate prediction responses. Freeze drying is used to avoid water interference and to increase FA concentrations; however, this process also increases cost of analysis. High NIR spectroscopy predictability can also be obtained when other pre-treatments are applied to meat, for example, prediction performances have been found to be much higher for fat extracts rather than intact samples.<sup>43</sup>

Prieto et al.<sup>31</sup> used NIR spectroscopy online in the abattoir to predict the FA profile of beef. These authors scanned the intact rib-eye area using a fiber optic contact probe and observed different NIR spectroscopy predictability between breeds, despite animals being managed, fed, and slaughtered in a similar manner. Prieto et al.<sup>31</sup> hypothesized that NIR spectroscopy was more accurate in predicting the FA profile of Limousin crossbred carcasses due to smaller adipocytes than those of Aberdeen Angus crossbred, as adipocyte size could vary spatial arrangements of intramuscular fat deposits in meat. Later, Prieto et al.<sup>33</sup> and Mourot et al.<sup>44</sup> tested the NIR spectroscopy ability using benchtop equipment to predict FA content of homogenized beef and found higher NIR spectroscopy predictability than Prieto et al.<sup>31</sup> on intact beef, which agrees with the results previously indicated for other species. Prieto et al.<sup>33</sup> and Mourot et al.<sup>44</sup> reported excellent NIR spectroscopy prediction equations for the content of SFA and MUFA, and suitable for screening purposes for conjugated linoleic acid (CLA). Nevertheless, unsuitable predictions were found for total PUFA, n-3, and n-6 FA content. These authors attributed the unsatisfactory predictions of PUFA to either an insufficient variability in the data (probably because of their structural function in membrane phospholipids) or a low concentration. As Azizian and Kramer<sup>45</sup> mentioned, a minimum threshold of FA content appears to be required to detect PUFA, which is not always reached. Nevertheless, Prieto et al.<sup>33</sup> indicated that the high NIR spectroscopy predictability for SFA and MUFA contents would allow for calculation of the PUFA concentration as the difference between the total FA predicted by NIR spectroscopy ( $R^2=0.97$ , RPD=4.70) and the sum of SFA and MUFA contents.

While scanning of intact meat samples would be ideal in making NIR spectroscopy a rapid and low-cost analytical technique to predict FA profile, the current calibration and prediction performances are still not adequate for practical use. When homogenized samples are used, robust calibrations are obtained when data sets with wide variability are available, but this condition is difficult to reach for FA that are found in a constant proportion. Additionally, sample grinding is a time-consuming step, and the commercial value of the beef and pork loin/chicken breast would be decreased if their integrity were lost due to analytical processing. Another limiting factor is the similar absorption patterns of different FA due to similarities in

chemical structure and functional groups (mainly  $-\text{CH}_2-$ ). These similar absorbances can make the prediction of FA with low concentrations difficult, as their effect on final spectra is relatively minor and their associated peaks can be obscured by other major FA with similar functional groups. Further research aimed at improving prediction accuracies of FA profiles from intact meat samples needs to be conducted. Nevertheless, from industry perspective, use of NIR spectroscopy as a noninvasive and rapid analytical technique for FA screening purposes might be of enough value for meat processors and manufacturers, and this possibility would need to be explored for use online under production conditions.

### *Prediction of Technological Parameters and Sensory Attributes*

Technological parameters such as water holding capacity, color, and pH are important meat quality characteristics that correlate with the sensory appreciation of meat by consumers.<sup>46</sup> Several studies have tested the NIR spectroscopy ability to quickly predict technological parameters in meat. As shown in Table 3, Vis-NIR spectroscopy was suitable for screening purposes for  $L^*$ <sup>47</sup> and  $L^*$ ,  $a^*$ , and  $b^*$  color values<sup>32</sup> when longissimus dorsi samples from pigs were scanned intact. However, Kapper et al.<sup>47</sup> did not find reliable Vis-NIR spectroscopy predictions for  $a^*$  and  $b^*$  color values in pork intact samples. Similar to the suggestion made above for prediction of chemical components, these authors indicated increasing the scanning area could have improved their prediction equations. However, scanning more area would likely increase scan time, which is limiting for practical application. In a parallel study under production plant conditions, Kapper et al.<sup>48</sup> scanned (833–2500 nm) intact the longissimus dorsi from pigs with a contact probe of approximately 4.5 cm<sup>2</sup>, covering the loin area of the sample. Nevertheless, NIR spectroscopy predictability for  $L^*$  color value was even lower than that reported at laboratory scale using benchtop equipment,<sup>47</sup> which could be due to the lack of visible region in the spectra. Additionally, Kapper et al.<sup>48</sup> indicated that each sample was only scanned once by the NIR spectroscopy device, suggesting scanning the sample multiple times may have improved the results. Again, increasing time required to scan each sample would limit the use of NIR spectroscopy under online conditions. In studies with beef, Prieto et al.<sup>33</sup> found unsatisfactory predictions for  $L^*$ ,  $a^*$ , and  $b^*$  color values when Vis-NIR spectroscopy spectra were collected on ground samples. Grinding samples prior to NIR spectra collection could have increased the rate of meat discoloration, resulting in reflectance differences between the visible region from the spectra and the objective color measurements. Additionally, for that study, there was an approximately 5 h time period between objective color measurement and NIR spectra collection. This delay likely

**Table 3.** Summary of applications of near infrared spectroscopy to predict technological and sensory characteristics in meat (sorted by species and publication year).

Calibration and prediction performance									
Species	Sample presentation	Attributes	Spectrometer spectral range (nm) Acquisition mode	Multivariate analysis	R <sup>2</sup> <sub>CAL</sub>	SECV	RPD	Reference	
Pig	Intact	pH	EPP2000	PLSR	0.80	0.11 <sup>†</sup>	2.1	Balage et al. (2015) <sup>32</sup>	
		Color L*	400–1395		0.88	2.02 <sup>†</sup>	2.3		
		Color a*	Reflectance		0.82	0.61 <sup>†</sup>	2.2		
		Color b*			0.80	1.07 <sup>†</sup>	2.1		
		WBSF (N)			0.48	5.51 <sup>†</sup>	1.2		
Pig	Intact	pH	NIRSystems6500	MPLS	0.39	0.2 <sup>†</sup>	1.3	Kapper et al. (2012) <sup>47</sup>	
		Color L*	400–2498		0.76	2.3 <sup>†</sup>	2.0		
		Color a*	Reflectance		0.54	1.2 <sup>†</sup>	1.4		
		Color b*			0.48	1.3 <sup>†</sup>	1.5		
		Drip loss (%)			0.80	0.8 <sup>†</sup>	1.9		
Pig	Intact	pH	Matrix-F FT-NIR	MPLS	0.37–0.65	0.1 <sup>†</sup>	1.1–1.3	Kapper et al. (2012) <sup>48</sup>	
		Color L*	833–2500		0.48–0.67	2.8–3.6 <sup>†</sup>	1.1–1.8		
		Drip loss (%)	Reflectance		0.58–0.76	0.7–1.1 <sup>†</sup>	1.5–2.1		
		pH	USB 4000		0.79–0.86	0.10–0.16	1.52–2.40		
Beef	Ground		350–1100	PLSR				Liao et al. (2010) <sup>30</sup>	
		Reflectance							
		pH	NIRSystems6500		0.73	0.09	1.14		Prieto et al. (2014) <sup>33</sup>
		Color L*	400–2498		0.80	1.27	1.69		
		Color a*	Reflectance		0.71	1.45	1.25		
		Color b*		0.77	0.77	1.56			
Beef	Intact/ Ground	Shear force 16 d (kg)			0.81	0.62	1.70	De Marchi et al. (2013) <sup>49</sup>	
		pH	LabSpec2500	0.62/0.42*	0.10/0.13	1.70/1.31			
		Color L*	350–1800	0.70/0.55*	1.97/2.39	1.87/1.54			
		Color a*	Reflectance	0.73/0.52*	1.37/1.82	1.89/1.43			
		Color b*		0.60/0.41*	1.33/1.64	1.59/1.29			
		Ageing loss (%)		0.15/0.12*	1.32/1.33	1.09/1.08			
		Cooking loss (%)		0.38/0.12*	3.02/3.50	1.23/1.06			
Beef	Intact	WBSF (N)	NIRSystems6500	PLSR	0.34/0.13*	9.39/10.74	1.24/1.09	Yancey et al. (2010) <sup>54</sup>	
		MORSf (N)	400–2498		0.56–0.86	3.15–4.15	1.13–1.50		
		WBSF (kg)	Reflectance		0.42–0.80	0.65–0.73	1.05–1.18		
		Tenderness			0.47–0.86	0.57–0.71	1.10–1.38		
		Overall impression			0.43–0.89	0.39–0.52	1.06–1.40		

(continued)

Table 3. Continued

Species	Sample presentation	Attributes	Spectrometer spectral range (nm) Acquisition mode	Multivariate analysis	Calibration and prediction performance				Reference
					R <sup>2</sup> <sub>CAL</sub>	SECV	RPD		
Chicken	Intact	pH	LabSpec2500 350–1800 Reflectance	PLSR	0.50*	0.09	1.42		De Marchi et al. (2011) <sup>50</sup>
		Color L*			0.48*	1.73	1.40		
		Color a*			0.77*	0.29	2.14		
		Color b*			0.86*	1.16	2.82		
		Thawing loss (%)			0.49*	1.00	2.14		
		Cooking loss (%)			0.58*	1.88	1.57		
		WBSF (N)			0.17*	3.18	1.20		

\*Coefficient of determination of cross-validation.

†Standard error of prediction.

WBSF, Warner-Bratzler shear force; MORSt, Meullenet-Owens razor shear force; PLSR, partial least squares regression; MPLSR, modified partial least squares regression; R<sup>2</sup><sub>CAL</sub>, coefficient of determination of calibration; SECV, error standard of cross-validation; RPD, ratio of performance deviation.

contributed to the lower reliability of those NIR spectroscopy predictions, as the oxidation states of myoglobin pigments in meat would have changed between measures, as well as color. Although more accurate predictions were reported on intact than in homogenized meat samples by De Marchi et al.,<sup>49</sup> as expected for color values, Vis-NIR spectroscopy calibration models for the prediction of L\*, a\*, and b\* color values on intact samples did not meet the requirements for screening purposes according to Williams.<sup>24,25</sup> Unlike previous studies in beef, De Marchi et al.,<sup>50</sup> using portable NIR spectroscopy equipment in the range of 350–1800 nm, found Vis-NIRS prediction suitable for screening purposes for a\* and b\* values on intact chicken breast, although unreliable prediction was observed for L\* value. Hence, the ability of NIR spectroscopy to predict L\*, a\*, and b\* has been found to be variable between studies, and this variability could be attributed to various factors including instrument capabilities and settings, number and types of samples, different species, statistical methods adopted, different ranges of wavelength in spectra collection, and local conditions (industry or laboratory) among others.

Regarding pH, Balage et al.<sup>32</sup> and Liao et al.<sup>30</sup> found NIR spectroscopy suitable for rough screening purposes for intact pork samples, whereas other authors have reported unreliable predictions for intact pork and chicken, and for both intact and homogenized beef.<sup>33,47–50</sup> As indicated by Prieto et al.,<sup>29</sup> the limited predictive ability of NIR spectroscopy models for pH could be caused by the low variation in measures for this trait. Additionally, pH values vary between samples and locations in the same muscle depending on the marbling.<sup>51</sup> This affects the repeatability of the reference method and jeopardizes the NIR spectroscopy predictability, especially when pH measurements and NIR spectra collection have been performed in different muscle locations. It is common practice to avoid the incision created from the pH-probe when collecting NIR spectra after pH measurements; this results in NIR spectra collection from a different muscle area. De Marchi et al.<sup>49</sup> observed a better prediction of pH when collecting spectra on intact rather than homogenized samples; probably due to a lack of information about the muscle structure (light scattering properties from intact muscle tissue) when scanning the samples after grinding.<sup>52</sup> Additionally, pH measures from intact meat are mainly from lean tissue, since effort is usually taken to avoid large intramuscular fat depositions when measuring pH. However, measures of pH obtained from ground samples contain information from both lean and fat, so pH values from the same muscle could vary according to sample preparation. These could be the reasons why Prieto et al.<sup>33</sup> did not find accurate NIR spectroscopy predictions for pH measured on intact meat when spectra were collected on homogenized samples.

Near-infrared spectroscopy has been tested to predict other technological traits such as water holding capacity

(measured as cooking, drip, thawing, or ageing losses). Acceptable NIR spectroscopy equations for screening purposes have been reported for drip loss in beef<sup>47,48</sup> and thawing loss in poultry meat.<sup>50</sup> Conversely, De Marchi et al.<sup>49,50</sup> did not find reliable predictions for ageing and/or cooking losses in beef and poultry meat. It is well known that NIR spectroscopy cannot directly predict ageing and cooking losses, but it may through the association of water holding capacity with water, fat (especially intramuscular), and protein wavelengths. Nevertheless, the heterogeneity of meat samples<sup>29</sup> and the low repeatability of measuring water holding capacity of meat<sup>53</sup> have been indicated as possible causes for the limited ability of NIR spectroscopy to predict ageing and cooking losses.

De Marchi et al.<sup>49</sup> and Prieto et al.<sup>33</sup> reported limited NIR spectroscopy ability to predict shear force of beef when spectra were collected on homogenized meat samples. Again, this could be attributed to homogenization prior to spectra collection, as clearly grinding will destroy the muscle structure and fiber arrangements. Nevertheless, NIR spectra collected from intact samples also did not yield accurate predictions in beef, pig, and poultry meat.<sup>32,49,50,54</sup> Shear force measures obtained from the same muscle can have a high variability due to muscle heterogeneity, thus making NIR spectroscopy prediction for this parameter difficult. Nevertheless, Balage et al.<sup>32</sup> observed a classification model that correctly categorized 72% of pork samples into tender and tough classes using Vis-NIR spectroscopy. These authors stated that a technology able to discriminate tender pork with such accuracy might be useful for industrial applications, as it could allow the high-quality meat to be rapidly identified for differentiated product lines. Additionally, the potential of NIR spectroscopy for online classification of beef carcasses for longissimus tenderness has been shown by Shackelford et al.,<sup>55</sup> who suggested that this technology may allow for tenderness-based beef merchandising systems.

Yancey et al.<sup>54</sup> used Vis-NIR spectroscopy regression equations for predicting consumer panel responses for tenderness and overall impression. These authors found better results when a second order derivative was applied to the spectra, where the percentage of variance explained by the model was over 85% for both tenderness and overall impression. Visible NIRS was more successful in the prediction of consumer responses for tenderness and overall impression than shear methods, Meullenet–Owens razor shear (MORS), and Warner–Bratzler shear force (WBSF). While the Vis-NIRS equations had similar accuracies in predicting tenderness and overall impression, the MORS and WBSF methods were better to estimate tenderness ( $R^2 = 0.38\text{--}0.58$ ) than overall impression ( $R^2 = 0.15\text{--}0.37$ ). Shear techniques are unable to predict aspects of overall impression such as juiciness and flavor. However, NIR values are obtained from vibration modes of chemical bonds within samples;<sup>6</sup> therefore, it is better able to

quantify moisture levels, protein quality, and possibly the presence of flavor compounds. Additionally, characteristics such as protein density, sarcomere length, and collagen cross-linking that influence tenderness might be detected using NIR spectroscopy. Hence, Yancey et al.<sup>54</sup> concluded that due to the ability to measure traits beyond tenderness and owing to the nondestructive manner through which measures can be obtained, Vis-NIRS may be a better alternative to traditional shear tenderness in predicting tenderness and overall impression from a consumer panel.

Despite recent improvements in NIR spectroscopy technology having increased its potential,<sup>47,48</sup> published results show NIR spectroscopy still has a limited ability to predict the technological and sensorial quality of meat. Nevertheless, NIR spectroscopy has shown some ability for screening or classification of meat based on some of these characteristics. However, it remains unknown if these classifications would be successful for online application in meat processing plants. As there is a need within the meat processing industry for further market segmentation to fulfil consumer desires for high quality products, efforts to control all the factors influencing the spectral data and the precision of reference methods are needed to improve the predictive/screening performance of NIR models for technological and sensory attributes of meat.

### Prediction of Carcass Fat Quality

In recent years, due to dietary recommendations put forth by the World Health Organization,<sup>56</sup> several strategies to enhance FA composition of animal products destined for human consumption (e.g., modulating genetics and diet) are being investigated.<sup>57,58</sup> However, the increased concentration of dietary unsaturated FA can have negative effects on fat quality. Porcine fat quality, for example, is an important factor for economic value, human nutrition, and taste. Increased concentrations of unsaturated FA can lead to soft fat, processing problems, reduced quality and shelf life of processed pork products, and an inability to meet fresh pork export specifications.<sup>59</sup> Consequently, soft fat is deemed undesirable in multiple countries, such as Canada,<sup>60</sup> the United States,<sup>61</sup> and the European Union.<sup>62</sup> In fact, soft fat is the main cause for downgrading and lowered price in Japan due to its reduced sliceability and lower processing quality,<sup>63</sup> particularly in bacon manufacturing. Beyond issues with fat softness, increased contents of unsaturated FA can also reduce oxidative stability and negatively affect the flavor of meat.<sup>64</sup>

Analyses to evaluate fat quality using standard methods, such as gas chromatography, demand a high level of technical expertise, are expensive, time-consuming, and require toxic solvents and reagents. Since NIR spectroscopy is rapid, relatively easy to use, and requires no chemical use, several authors (Table 4) have evaluated its potential to predict the FA composition in pig carcasses. In addition



**Table 4.** Summary of applications of NIR spectroscopy to predict carcass fat and meat product quality (sorted by product and publication year).

Product	Sample presentation	Attributes	Spectrometer spectral range (nm) Acquisition mode	Multivariate analysis	Calibration and prediction performance			
					R <sup>2</sup> <sub>CAL</sub>	SECV	RPD	Reference
Pork subcutaneous fat	Intact	Iodine value	LabSpec4	PLSR	0.95	1.03 <sup>†</sup>	3.61	Prieto et al. (2016) <sup>70</sup>
		SFA (%)	350–2500		0.88	0.82 <sup>†</sup>	2.55	
		MUFA (%)	Reflectance		0.85	0.90 <sup>†</sup>	2.18	
		PUFA (%)			0.94	0.62 <sup>†</sup>	3.54	
		Omega-3 (%)			0.93	0.36 <sup>†</sup>	3.09	
Pork subcutaneous fat (Cold/Warm)	Intact	Omega-6 (%)			0.89	0.62 <sup>†</sup>	2.54	Prieto et al. (2014) <sup>67</sup>
		Iodine value	NIRSystem6500	PLSR	0.90/0.87	1.66/1.80	2.54/2.42	
		SFA (%)	400–2498		0.89/0.86	1.11/1.37	2.68/2.27	
		MUFA (%)	Reflectance		0.86/0.82	1.11/1.23	2.17/1.96	
		PUFA (%)			0.89/0.86	0.97/1.08	2.47/2.16	
Pork subcutaneous fat	Intact	Omega-3 (%)			0.82/0.80	0.25/0.26	2.08/2.04	Sorensen et al. (2012) <sup>71</sup>
		Omega-6 (%)			0.86/0.83	0.94/1.03	2.18/2.02	
		Iodine value	NirFom	iPLSR	0.83	1.44	2.35	
			1100–2200					
			Transmittance					
Pork subcutaneous fat	Small pieces/ Melted fat in a microwave	Iodine value	FoodScan	MPLSR	0.98	0.57	6.8	Gjerlaug-Enger et al. (2011) <sup>66</sup>
		SFA (%)	850–1050		0.98	0.38	7.1	
		MUFA (%)	Transmittance		0.95	0.45	4.2	
		PUFA (%)			0.98	0.28	6.5	
Pork subcutaneous fat	Intact (Longitudinal/ Transversal cuts)	SFA (%)	Matrix-F FT-NIR	PLSR	0.85/0.80	1.71/1.9 <sup>†</sup>	2.33/2.08	Perez-Juan et al. (2010) <sup>68</sup>
		MUFA (%)	909–2500		0.92/0.88	1.2/1.2 <sup>†</sup>	3.99/3.99	
		PUFA (%)	Reflectance		0.77/0.74	1.6/1.4 <sup>†</sup>	1.94/2.21	
Pork dry-cured sausages	Ground	SFA (%)	NIRSystem6500	MPLSR	0.94	0.98	2.63	Fernandez-Cabanas et al. (2011) <sup>74</sup>
		MUFA (%)	400–2498		0.78	1.47	1.45	
		PUFA (%)	Reflectance		0.83	0.88	1.58	
Thai steamed pork sausages	Intact (Plastic casing/ Non-plastic casing)	Moisture (%)	MPA FT-NIR	PLSR	0.92–0.98/	0.79–2.67/	1.46–4.92/	Ritthiruangdej et al. (2011) <sup>73</sup>
		Protein (%)	800–2500		0.98–0.98	0.76–2.05 <sup>†</sup>	2.08–5.62	
			Reflectance		0.65–0.96/	0.68–1.33/	1.54–3.0/	
					0.44–0.97	0.57–1.78 <sup>†</sup>	1.15–3.41	
					0.87–0.91/	1.71–2.31/	1.99–2.69/	
		Fat (%)			0.90–0.94	1.51–1.99 <sup>†</sup>	2.31–3.06	
					0.61–0.70/	0.19–0.20/	1.13–1.20/	
		Ash (%)			0.19–0.99	0.11–0.27 <sup>†</sup>	1.05–2.45	
					0.93–0.94/	2.22–4.67/	1.17–2.45/	
		Carbohydrate (%)			0.92–0.96	2.15–2.65 <sup>†</sup>	1.90–2.34	

(continued)

Table 4. Continued

Product	Sample presentation	Attributes	Spectrometer spectral range (nm) Acquisition mode	Multivariate analysis	Calibration and prediction performance			
					R <sup>2</sup> <sub>CAL</sub>	SECV	RPD	Reference
Fermented pork sausages	Intact (On-contact/Remote probe)	Moisture (%)	Matrix-F FT-NIR 830–2500 Reflectance	PLSR	0.997/0.998	0.675/0.622 <sup>†</sup>	19.8/21.6	Collell et al. (2010) <sup>77</sup>
		Water activity			0.991/0.987	0.006/0.007 <sup>†</sup>	9.2/8.3	
Smoked and dry-cured pork	Ground	NaCl (%)	NIRSystem5000 1100–2500 Reflectance	PLSR	0.981/0.994	0.117/0.116 <sup>†</sup>	6.2/6.2	Boschetti et al. (2013) <sup>82</sup>
		Moisture (%)			1.00	1.0	6.9	
		Water activity			1.00	0.4	9.1	
		NaCl (%)			0.86	8.2	2.7	
		Protein (% DM)			1.00	1.4	2.0	
		Fat (% DM)			1.00	11.4	2.8	
Dry-cured pork	Ground	Ash (% DM)	NIRSystem6500 400–2500 Reflectance	PLSR	1.00	2.1	7.5	Prevolnik et al. (2011) <sup>75</sup>
		Moisture (g/kg)			0.86–0.90	4.90–6.58	2.18–2.88	
		Salt (g/kg)			0.96–0.97	1.60–2.28	3.12–4.57	
		Protein (g/kg)			0.81–0.84	0.59–0.63	1.82–1.94	
		Non-protein nitrogen (g/kg)			0.76–0.89	0.38–0.47	1.74–2.06	
		Proteolysis index (%)			0.72–0.82	0.84–0.97	1.58–1.78	
		Intramuscular fat (g/kg)			0.88–0.91	3.08–3.91	2.46–2.97	
		Free amino acids (mg/100 g DM)			0.63–0.93	358–656	1.29–2.30	
		NaCl (%)			0.64–0.98/0.81–0.99	0.07–0.13/0.08–0.17	1.27–5.71/1.78–6.56	
					MPLSR			
Several meat products	Intact/ Ground		FoodScan 850–1050 Transmittance					De Marchi et al. (2017) <sup>83</sup>

\*Coefficient of determination of cross-validation.

<sup>†</sup>Standard error of prediction.SFA, saturated fatty acids; MUFA, monounsaturated fatty acids; PUFA, polyunsaturated fatty acids; DM, dry matter basis; FT, Fourier transformation; PLSR, partial least squares regression; iPLSR, interval partial least squares regression; MPLSR, modified partial least squares regression; R<sup>2</sup><sub>CAL</sub>, coefficient of determination of calibration; SECV, error standard of cross-validation; RPD, ratio of performance.

to using NIR spectroscopy to estimate FA profile, researchers have attempted to predict iodine value (IV) in pork subcutaneous fat. The IV is an estimate of the proportion of unsaturated FA in a sample and, therefore, correlates to carcass fat firmness.<sup>65</sup> Gjerlaug-Enger et al.<sup>66</sup> reported excellent NIR spectroscopy equations to predict proportions of FA groups and IV from pig fat using benchtop equipment scanning 850–1050 nm, whereas Prieto et al.<sup>67</sup> observed that NIR spectroscopy was only suitable for screening purposes despite using laboratory equipment capable of scanning the full Vis-NIR range (400–2498 nm). Perez-Juan et al.<sup>68</sup> successfully predicted the content of MUFA in pork ham fat scanning (909–2500 nm) longitudinal and transversal cuts, albeit SFA and PUFA predictions were only adequate for screening. The better NIR spectroscopy performance in the former study could be because the fat samples were processed before NIR scanning either by cutting into small pieces or melting fat in a microwave, whereas in the latter study the fat was scanned intact. Fat samples from Gjerlaug-Enger et al.<sup>66</sup> were, therefore, more homogeneous, and tissue homogeneity is an important factor for maximizing NIR spectroscopy predictability.<sup>29</sup> Similar results were observed by Zamora-Rojas et al.<sup>69</sup> when predicting individual FA (data not shown), who reported better predictions for individual FA when fat samples were melted before scanned in transreflectance mode using laboratory equipment ( $R^2=0.95\text{--}0.99$ ,  $\text{SEP}=0.19\text{--}0.51\%$  of total FA) compared to scanning intact adipose tissue ( $R^2=0.93\text{--}0.98$ ,  $\text{SEP}=0.31\text{--}1.25\%$  of total FA). Additionally, NIR spectroscopy predictability using benchtop equipment was higher than when using a handheld micro-electro-mechanical system (MEMS)-based NIR spectrometer on transverse subcutaneous adipose tissue sections scanned directly on the carcasses ( $R^2=0.81\text{--}0.87$ ,  $\text{SEP}=0.55\text{--}1.30\%$  of total FA). However, aforementioned sample preparation procedures would be impractical for online measurements under commercial conditions. Therefore, efforts have recently been made to test the ability of NIR spectroscopy under real-time conditions. Prieto et al.<sup>70</sup> accurately predicted the IV and some groups of FA in pork subcutaneous fat when portable NIR spectroscopy equipment fitted with a fiber optic contact probe was used online in a Canadian federally inspected abattoir, where spectra were captured directly in real time without interrupting carcass processing. A lower predictability for IV in pork fat, although still suitable for screening purposes, was reported by Sorensen et al.<sup>71</sup> who developed an online method based on NIR transmission spectroscopy and refined by chemometrics at full abattoir processing speed (approximately 1000 carcasses per hour). Hence, the potential of NIR spectroscopy technology to quickly and accurately estimate the IV of subcutaneous fat on the carcass, immediately after slaughter and without sample treatment, opens new possibilities for the subsequent ability to sort pork carcasses according to fat hardness for marketing purposes. Such an approach would

replace the need for destructive and time-consuming techniques to measure IV chemically. In addition, providing this information to pig producers and the feed industry may allow for genetic selection and diet formulation aimed at improving fat quality. The use of NIR spectroscopy could also lead to the inclusion of IV in payment systems. For example, Switzerland has successfully implemented IV in their payment system for pork, where the suppliers of finished pigs receive payment deductions when a carcass has an  $\text{IV} > 62$ .<sup>72</sup>

### Prediction of Meat Products Quality

Regarding the recent use of NIR spectroscopy on meat products (Table 4), Ritthiruangdej et al.<sup>73</sup> used Fourier transform (FT)-NIR spectroscopy on spectra collected in reflectance to estimate chemical composition of steamed pork sausages. Using an external validation, prediction accuracy was highest for moisture followed by protein, fat, carbohydrate, and ash; with sufficient accuracy for quality control for moisture and adequate for screening of protein and fat content. The NIR spectroscopy predictability was similar when the sausages were packed and scanned through the packaging. These results indicated that plastic casing does not have a large impact on the building of PLS models, and that unwanted light scattering effects were adequately reduced from NIR spectra using the MSC treatment. This is a great advantage for NIR spectroscopy to be implemented by the industry as a nondestructive method for rapid analysis of chemical composition of steamed pork sausages. Ritthiruangdej et al.<sup>73</sup> observed different prediction accuracies according to the mathematical treatment used, where prediction results were worse from second derivative mathematical pre-processing. According to these authors, the reason for the apparent breakdown could be explained as the non-monotonic amplification scatter substantially induced by the physical structure of sausages. Such scattering is better managed by MSC transformations than second derivatives; the latter appear to enhance differences in the physical structure of these meat products creating irrelevant variation of spectral intensity. The second derivative has been most commonly used as a pre-treatment method for NIR spectra, and sometimes maybe without consideration as to why it may or may not be suitable. However, the results from Ritthiruangdej et al.<sup>73</sup> suggest that physical structure of the samples is important to consider, so that the adequate mathematical treatment to spectra collected in reflectance is applied.

Fernandez-Cabanas et al.<sup>74</sup> estimated the FA profile in pork dry-cured sausages by NIR spectroscopy and found prediction equations suitable for screening purposes for SFA, but unsatisfactory for unsaturated FA. Sausages have a complex physical matrix composed of meat and fat mixtures obtained from different anatomical regions and

potentially different animal species. Hence, developing adequate NIR calibrations for complex products and non-conventional analytical parameters will require a large number of samples in the calibration set attempting to increase the variation for the FA studied. For example, adding samples from animals fed different diets will vary their FA profiles. Nevertheless, these authors indicated that NIR spectroscopy could be useful for the rapid quality control of dry-cured sausages, allowing for an estimation of the major constituents and/or potentially allow classification of sausages based on FA profiles. This information could also be used to estimate sausage shelf life and for additional nutritional labeling. Alternatively, fats could be pre-screened for their composition prior to adding to the sausage blend, allowing the opportunity to develop sausages with healthful FA profiles.

Prevolnik et al.<sup>75</sup> used Vis and/or NIR range to predict chemical composition, salt content and free amino acids in dry cured ham, and observed no major differences in the prediction of chemical constituents between NIR or the entire spectral range (Vis-NIR). Indeed, when visible spectra were tested alone, the models had lower prediction accuracy. When using NIR spectral data, excellent NIR spectroscopy prediction equations were obtained for salt content and salt percentage in moisture/dry matter, satisfactory for moisture, non-protein nitrogen, intramuscular fat, and total free amino acids, while unsuccessful for protein content and proteolysis index. Individual free amino acid predictions had variable success, with comparable results from external validation. The most accurate predictions from this study were obtained for salt content, despite the inability of NIR spectroscopy to detect inorganic substances<sup>76</sup> unless they are bound to organic substances. As such, it is likely that salt (NaCl) content in dry-cured ham is indirectly predicted from other compounds (e.g., correlation coefficient between salt and water content was 0.53 in Prevolnik et al.)<sup>75</sup> and/or different quality properties. While NaCl itself is not absorbed in the NIR region, different dissolved salt concentrations cause wavelength shifts in the spectrum. Unfortunately, the same effect can be caused by changes to sample temperature;<sup>70</sup> hence, these models for predicting NaCl are temperature-dependent. In the case of proteins, the protein content was calculated assuming all nitrogen in the sample is in protein; however, a portion (27%) of nitrogen is not associated with protein. Thus, this discrepancy between reference method and spectral data could partly explain the lower NIR spectroscopy predictability for the protein content. Based on those results, Prevolnik et al.<sup>75</sup> concluded that NIR spectroscopy could replace chemical methods in quality control of dry-cured ham.

Collell et al.<sup>77</sup> tested the feasibility of NIR spectroscopy for predicting parameters related to the drying process of fermented sausages, by acquiring spectra through two NIR setups with contact and remote probes. These authors

reported an outstanding NIR spectroscopy predictability for moisture content and excellent for water activity and NaCl content with both setups. Production of high-quality fermented sausages requires strict control during the drying and ripening processes; inadequate control during these processes can cause texture problems including crust formation.<sup>78</sup> Several studies have demonstrated there is a relationship between textural problems with superficial water activity, moisture, and NaCl contents.<sup>79,80</sup> Thus, monitoring of these parameters at the surface of the product online would be useful in order to prevent crusting,<sup>81</sup> and NIR spectroscopy could be a successful technology for online monitoring of drying processes. Boschetti et al.<sup>82</sup> reported similar NIR spectroscopy ability to predict water activity and lower, but still reliable, for NaCl, moisture, fat, and ash content in a smoked and dry-cured pork product (Bauernspeck) using a benchtop instrument. More recently, De Marchi et al.<sup>83</sup> successfully predicted NaCl proportion by NIR spectroscopy in a wide range of processed meat products (cured meat, boiled sausages, dry meat, and bacon), showing better predictability when spectra were collected on ground than on intact meat products due to the lower percentage of outliers in the former.

From the studies previously mentioned, it is apparent NIR spectroscopy has the potential for accurately predicting and/or quickly screening different quality attributes of meat products. Near-infrared spectroscopy has become a powerful analytical tool especially suited for quantitative estimation or qualitative classification of multi-component systems such as meat products and, therefore, could replace chemical methods in quality control processes.

### *Classification and Identification of Meat and Meat Products*

Many consumers place emphasis on non-compositional aspects of meat related to quality, such as intrinsic characteristics of animals (species, breed), geographical origin, feeding system, or post-mortem strategies. As opportunities to provide differentiated meat and meat products with enhanced quality attributes are expanding<sup>84</sup> and consumers are willing to pay premiums for such products, potential for fraud may exist. In order to guarantee that consumers are not being defrauded in the purchase of meat and meat products making claims of quality, origin, or species, authorities require tools to rapidly and successfully distinguish those meat and meat products.

As shown in Table 5, NIR spectroscopy has been used for species identification purposes. Mamani-Linares et al.<sup>85</sup> used NIR spectroscopy to successfully identify cattle, llama, and horse meat from homogenized meat and meat juice samples (89–100% of samples correctly classified). Restaino et al.<sup>86</sup> discriminated meat pates according to animal species, with 100% of the beef and pork samples correctly classified. Likewise, Schmurtzler et al.,<sup>87</sup> using

**Table 5.** Summary of applications of NIR spectroscopy to classify meat and meat products (sorted by species and publication year).

Species	Research purpose	Sample presentation	Spectrometer spectral range (nm) Acquisition mode	Multivariate analysis	Correctly classified (%)	Reference
Pork	Discrimination of enhanced quality pork	Intact	LabSpec4 350–2500 Reflectance	PLS-DA	Lacombe: 94/ Duroc: 95/ Iberian: 100 (aged 2 days)	Prieto et al. (2015) <sup>90</sup>
					Lacombe: 94/ Duroc: 98/ Iberian: 100 (aged 14 days)	
					ME: 97/ Non-ME: 99 (aged 2 days)	
					ME: 94/ Non-ME: 95 (aged 14 days)	
					Aged 2 days: 94/ aged 14 days: 97 Control/ Canola/ Flaxseed: n/a (aged 2 and 14 days)	
Pork	Classification of pig carcasses based on feeding regime	Intact	MEMS-NIR 1600–2400 Reflectance	PLS-DA	BC: 54/ Non-BC: 57 (aged 2 days)	Zamora-Rojas et al. (2012) <sup>91</sup>
					BC: 54/ Non-BC: 53 (aged 14 days)	
Pork	Discrimination of pork storage time (from 1 to 6 days)	Intact	Antaris II FT-NIR 1000–2500 Reflectance	LDA KNN BP-ANN	Acorn: 94/ Feed: 96/ Recebo: 61	Chen et al. (2011) <sup>94</sup>
					89	
					92	
Pork	Pork meat classification based on five quality groups	Intact	FieldSpec 350–2500 Reflectance	DISCRIM	96	Monroy et al. (2010) <sup>93</sup>
					RFN: 70–88	
					RSE: 57–83	
Beef	Discrimination of dark cutters	Intact	LabSpec4 350–2500 Reflectance	PLS-DA	PFN: 67–84	Prieto et al. (2014) <sup>92</sup>
					PSE: 65–100	
					Normal: 95	
					Dark cutters: 95	
Lamb	Classification of lamb meat based on geographical origins	Intact	DA7200 950–1650 Reflectance	PLS-DA	Normal: 88	Sun et al. (2012) <sup>89</sup>
					Dark cutters: 90	
					Pastoral and agricultural region: 100	
					Specific regions: 89	
				LDA	Pastoral vs. agricultural region: 100	
					Specific regions: 75	

(continued)



Table 5. Continued

Species	Research purpose	Sample presentation	Spectrometer spectral range (nm) Acquisition mode	Multivariate analysis	Correctly classified (%)	Reference
Pork + veal	Analysis of pork adulteration in veal sausages	Intact	NIRFlex N-500 1659–1825 Reflectance MicroPhazir GP 4.0 1656–1802 Reflectance	PCA SVM	Genuine vs. 50% adulteration: 100 Genuine vs. 40% adulteration: 100 Genuine vs. 30% adulteration: 100 Genuine vs. 20% adulteration: 100 Genuine vs. 10% adulteration: 100	Schmurtzler et al. (2015) <sup>87</sup>
Several species	Identification of cattle, llama, and horse meat	Ground meat/Meat juice	NIRSystem6500 400–2500 Reflectance	PLS-DA	Beef: 100/95 Llama: 95/100 Horse: 89/95	Mamani-Linares et al. (2012) <sup>85</sup>
Several species	Discrimination of meat pates according to the animal species	Ground	NIRSystem6500 1100–2500 Reflectance	PCA	Beef: 100 Pork: 100 Binary mixtures: 72	Restaino et al. (2011) <sup>86</sup>

MEMS, micro-electro-mechanical systems; PLS-DA, partial least square discriminant analysis; LDA, linear discriminant analysis; KNN, K-nearest neighbors; BP-ANN, back propagation artificial neural network; DISCRIM, discriminant procedure in SAS; SVM, support vector machines; PCA, principal component analysis; ME, moisture enhanced; BC, blast chilled; n/a, not applicable; RFN, reddish-pink, firm, and non-exudative; RSE, red, soft, and exudative; PFN, pale, firm, and non-exudative; PSE, pale, soft, and exudative.

three setups (laboratory, industrial, and on-site), showed that NIR spectroscopy can be used to detect the presence of pork in veal sausage with a contamination level as low as 10%. This application could be used for Halal or Kosher verification purposes, which are increasingly becoming mandatory. Due to religious concerns, the presence of pork derivatives in food products is a serious matter, as some faiths forbid consumption of foods containing pork or its derivatives.<sup>88</sup>

Another application of NIR spectroscopy has been to classify meat based on geographical origin. Sun et al.<sup>89</sup> reported that NIR spectroscopy, together with the application of partial least squares discriminant analyses (PLS-DA) and LDA, correctly classified 100% of lamb meat from both pastoral and agricultural region samples. Additionally, 88.9% pastoral and 75% agricultural samples were correctly identified to the five individual regions where samples were obtained. Hence, these authors concluded that NIR spectroscopy combined with chemometrics could effectively and rapidly distinguish lamb meat by geographical origin.

Prieto et al.<sup>90</sup> using PLS-DA based on Vis-NIR spectra, observed that NIR spectroscopy could successfully classify pork according to pig breed, moisture enhancement of loins, and ageing duration. However, Vis-NIRS technology was not able to differentiate pork samples based on diet or carcass chilling process in that study. That lack of success of NIR spectroscopy to classify pork based on feeding regime is in disagreement with that shown by Zamora-Rojas et al.,<sup>91</sup> who found NIR spectroscopy technology was able to successfully classify Iberian pig carcasses by feeding regime (>90% of the sample classifications were correct). Differences between the results of these studies could be attributed to diet treatments (grass and acorns fed free-range pigs, acorns and grass supplemented with compound feeds in an outdoor system, and compound feeds using an intensive feeding system<sup>91</sup> versus animals fed a normal Canadian commercial diet, a high-oleic diet, or a high linolenic diet<sup>90</sup>), the diet durations (over 60 days versus 3 weeks), or which tissues were scanned (subcutaneous fat versus meat). Additionally, Prieto et al.<sup>90</sup> used canola and flaxseed diets formulated to increase FA beneficial for human health. Hence, it was expected the largest differences between diets would be in fat tissue. In that study, the meat samples scanned had around 2.6% of intramuscular fat (2.70% in the Control, 2.53% in the Canola, and 2.57% in the Flaxseed pork samples), which could in part explain why Vis-NIR spectroscopy classification was unsuccessful.

Additionally, Vis-NIR spectroscopy has shown the ability to classify beef and pork into quality grades. Prieto et al.<sup>92</sup> successfully discriminated dark cutters from normal beef using homogenized meat scanned with benchtop equipment and intact meat scanned using portable Vis-NIR spectroscopy (88–95% of samples were correctly classified). Monroy et al.<sup>93</sup> classified pork meat into four quality

groups (RFN: reddish-pink, firm, and non-exudative; RSE: red, soft, and exudative; PFN: pale, firm, and non-exudative; and PSE: pale, soft, and exudative) using different validation approaches, where the highest percentages of samples correctly classified were in the range of 83–100. Studies conducted to date, therefore, clearly show the potential of using Vis-NIR spectroscopy in beef and pork for classification purposes.

Another recent application of NIR spectroscopy has been in the area of meat shelf life. Chen et al.<sup>94</sup> used FT-NIR spectroscopy and different algorithms to discriminate pork based on storage time. These authors observed that the performance of a back propagation artificial neural network (BP-ANN) model was superior to LDA and KNN, with discrimination rates of the BP-ANN model of 99.26% and 96.21% in the training and prediction sets, respectively. Hence, these authors concluded that the discrimination rates obtained using FT-NIR spectroscopy combined with BP-ANN classification algorithm demonstrated this technique could potentially be used to classify pork based on storage time and freshness accordingly.

Although sometimes the visual examination of NIR spectra cannot discriminate between authentic and adulterated meat products,<sup>95,96</sup> the application of NIR spectroscopy together with statistical packages and multivariate data analysis techniques such as discriminant analysis (e.g., PLS-DA) has improved the understanding of the optical properties of meat. This has allowed classification of samples without chemical information.<sup>97</sup> The NIR spectroscopy can therefore be used for initial screening in the food chain to guarantee the quality/authenticity of meat and meat products for consumers; thus, more costly and time-consuming methods would only be required for samples that do not pass initial NIR spectroscopy screening.

## Conclusion and Future Outlook

The number of published studies on the application of NIR spectroscopy in the area of meat science has been increasing in recent years, as this technique has the advantages of being applied rapidly without further sample preparation. Many of the studies surveyed in this review show NIR spectroscopy can be a powerful analytical tool especially suited for quantitative estimation of quality attributes in intact/homogenized adipose tissue and multicomponent systems such as meat products and, therefore, could have the potential to replace chemical methods in quality control processes. Near-infrared spectroscopy could also have a role in increasing consumer confidence in meat and final meat products by confirming integrity, particularly identifying enhanced quality meat and confirming authenticity of species and geographical origin. Although NIR spectroscopy can successfully predict chemical composition of ground meat, limited ability has been shown for unprocessed meat samples, where prediction performances for meat

quality attributes are still not accurate enough for practical use. Nevertheless, from an industry perspective, use of NIR spectroscopy as a noninvasive, chemical-free, and rapid analytical technique for screening purposes might be of enough value for meat processors and manufacturers, and would need further exploration for online implementation.

The application of NIR spectroscopy has known advantages (lower costs; rapid, in situ, and nondestructive analyses; multi-parameter estimation; and environmental friendliness). However, there are several drawbacks and challenges associated with using this technology, such as sample presentation, which may become a crucial issue when scanning intact meat samples due to their heterogeneity and high absorbance of water in the infrared region. Collection of several spectra from the same sample, in order to increase the scanned area, could partly solve this issue. Nevertheless, this practice can hamper the online implementation of NIR spectroscopy, where scanning time is a limiting factor for industrial applications. Hence, further improvements of NIR spectrometers (e.g., equipped to scan larger areas to reduce the sampling error) are still necessary before industrial implementation can be considered. This would also have to be achieved without significant added cost to the equipment. Although measurement costs are low using the NIR spectroscopy technique, instrument costs are high meaning practical applications may still be restricted by cost. Researchers and analysts are therefore looking for sensitive wavelengths in the NIR region representing characteristics of food products, allowing for development of simpler and more specialized instruments at a lower cost. If successful, the applications of NIR spectroscopy may become more widely used and popular in many meat industries. Nevertheless, when reducing the wavelength range the possibility of assessing several attributes simultaneously is also constricted.

Some studies reported in this review show potential for portable instruments; however, most research has been performed under laboratory conditions or in research abattoirs. Therefore, it is difficult with the current data to evaluate the real performance of portable NIR spectroscopy devices in industrial settings. Online measurements at industrial levels remain challenging due to major influences of temperature fluctuations or moving samples; therefore, further work is still required to refine these instruments so they can be used easily under production conditions. Hence, development of a lower cost and a more rugged NIR instrument is necessary to integrate this technology in the meat production process.

The combination of techniques using different detection methods is a significant perspective for the use of NIR spectroscopy in meat and meat product industries, since it would be probably more cost effective and reduce the time needed for traditional (i.e., multiple and separate) analyses. Additionally, it is an alternative way to overcome some of the limitations of techniques (e.g., NIR

spectroscopy is not sensitive to the mineral content). Therefore, the combination of NIR spectroscopy with other detection techniques, such as dual energy X-ray absorptiometry (DEXA), would allow estimation of not only chemical components and meat quality attributes but also whole carcass composition (fat, lean, and bone tissue content). Next-generation NIR spectrometers may also have potential to be implemented in smartphones. As a consequence, future research for quality control applications in carcass, meat and meat products will likely focus on using NIR spectroscopy combined with other nondestructive technologies and the implementation of portable, low-cost next-generation NIR instruments.

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