Meat and Muscle Biology™

Fraud Detection in Meat Using Hyperspectral Imaging

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Abstract: Fraud detection in meat is a challenging task for researchers, consumers, industries, and regulatory agencies. Traditional approaches for fraud detection are time-consuming, complicated, laborious, and expensive; they require technical skills. Therefore, much effort has been devoted in academia and industry to developing rapid and nondestructive optical techniques for fraud detection in meat. Among them, hyperspectral imaging has gained enormous attention and curiosity throughout the world. Hyperspectral imaging is an emerging analytical technique that combines spectroscopy and imaging in one system to acquire spectra and spatial information from an object simultaneously. Hyperspectral imaging is the only analytical technology that answers commonly asked analytical questions such as what chemical species are in the samples, how much, and most importantly, where they are located. Therefore, the technology will undoubtedly play indispensable roles in research and industry for fraud detection in the coming days.

Key words: hyperspectral imaging, adulteration, fraud detection, minced meat, machine learning
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Introduction

Food fraud or adulteration is an age-old problem. It has existed as long as food has been made and sold. Since prehistoric times, humans have altered the state of food to extend its longevity or improve its taste. Now, it has become a global issue. Major food adulteration events seem to occur regularly (Ellis et al., 2012). Over 1,300 cases of food adulteration have been documented from 1980 to 2010 (Moore et al., 2012), whereas 4,098 incidents of food fraud have been recorded (Figure 1) between 2010 and 2020 (Hellberg et al., 2021). Therefore, food fraud has increased many times since 2010. Unfortunately, the authors reported only the major incidents. Thus, the full scale of adulteration is not well documented because most incidents go undetected or unreported. On the other hand, the occurrence of fraud is not easy to evaluate without using highly sophisticated analytical tools (Ballin and Lametsch, 2008).

In today's marketplace, the food supply chain is now more global and complex than ever. Nowadays, most food no longer follows a straight line from producers and distributors to consumers. Therefore, tracing the source of adulteration, deliberate or accidental, has become more challenging. Around 50 years ago, the average grocery store stocked about 200 food items, most of which were grown, produced, or processed within 100 miles of the store. However, currently, the average supermarket stocks about 39,000 items, which have traveled an average of 1,500 miles, making detection harder and adulteration easier (Kamruzzaman, 2016). Therefore, increasingly globalized food supply chains and the economic motivation to provide cheaper food products have contributed to food adulteration (Kamruzzaman, 2016).

Minced meat is a very popular and versatile meat product in industrialized countries. It is also a significant ingredient in various high-value meat products such as hamburgers, patties, meatballs, sausages, and salami. Because of its high prices, minced meat and its different products can be attractive targets for economic adulteration. Such economic adulteration is practiced in many ways, such as replacement or partial

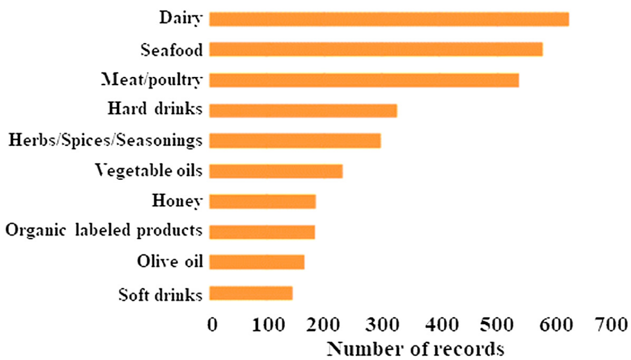

Figure 1. Documented records of food fraud between 2010 and 2020 (Hellberg et al., 2021).

replacement of high-value meat by low-cost meat or offals (Cozzolino and Murray, 2004). There are 2 staple reasons why it is challenging to identify adulteration in minced meat without sophisticated sorting analytical techniques: (1) mincing removes the morphological structures of meat muscle, and (2) the adulterated components are usually very similar to the authentic product. In 2013, the horsemeat scandal in Ireland and the United Kingdom drew huge attention both locally and globally to meat adulteration. The meat labeled as beef was found to contain undeclared horsemeat as well as meat from pork. This led to the recall of more than 10 million beef burgers and other beef products from supermarkets throughout Ireland and the UK (Boyacı et al., 2014). Although there is no significant safety concern for this type of adulteration, this is commercial malpractice. Therefore, the determination of authentication and detection of adulteration are indispensable for the minced meat industry. A variety of standard analytical methods (chromatography, electrophoretic separation of proteins, immunological procedure, and DNA-based techniques) can be used to identify and authenticate minced meat (Mousa et al., 2021). However, these techniques are invasive, time-consuming, laborious, and demand highly skilled personnel, and thus, they are not suitable for online application and routine analysis. In general, these purposes need to be specific, sensitive, rapid, and economical, analyze various meat products, and provide quantitative results (Meza-Márquez et al., 2010). Consequently, a cost-effective, efficient, rapid, and reliable method is required. Specifically, there is a great interest in developing optical technologies that can monitor in real-time assessment. Recently, hyperspectral imaging techniques have received considerable attention for authenticity and adulteration detection in minced meat (Rady and Adedeji, 2020; Jiang et al., 2021). Hyperspectral imaging combines the advantages of both spectroscopy and imaging techniques in one system to acquire spatial and spectral information from an object while overcoming the drawbacks of both methods when used alone. The power of spectroscopy is used to detect or quantify chemical constituents based on their spectral signature, and imaging transforms this information into chemical maps in the form of concentration profiles (Kamruzzaman and Sun, 2016). The hyperspectral imaging technology has the potential to apply offline, atline, online, and inline, provided that accurate calibration models can be constructed using high-dimensional multivariate data (Kamruzzaman et al., 2015).

Methodology

Hyperspectral imaging system

The configuration of a typical hyperspectral imaging system is shown in Figure 2. A typical hyperspectral imaging system comprises a light source that illuminates

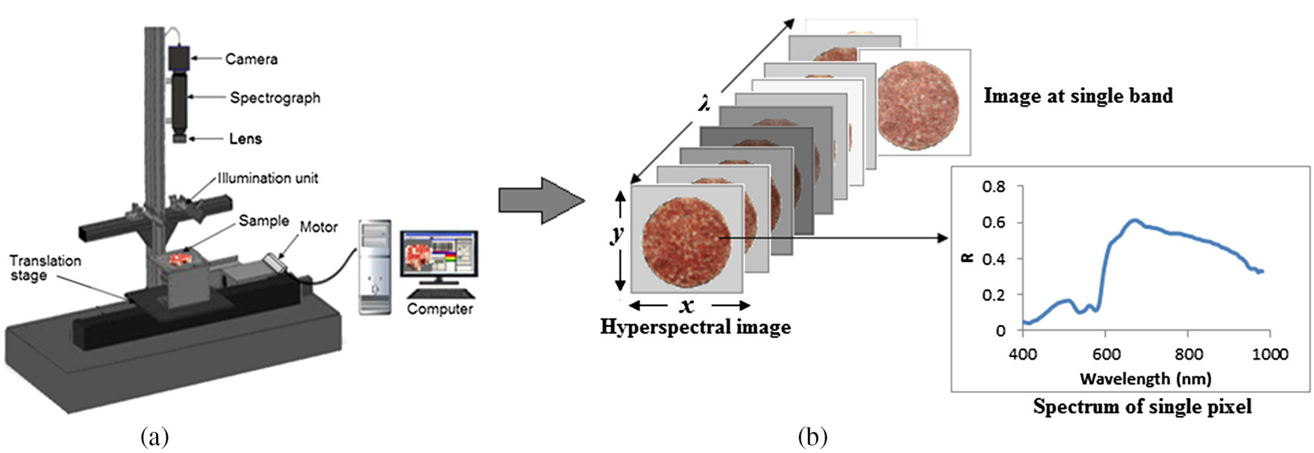

Figure 2. (A) Components of a typical hyperspectral imaging system and (B) the conceptual view of a hypercube comprising spatial (x and y) and spectral (λ) dimensions (Kamruzzaman, 2016).

the object, a lens to ensure sufficient focus and allocate the field of view, a spectrograph (wavelength dispersion unit) to split the light into various spectral wavelengths, a 2-D camera (detector) to capture the spatial-spectral images, and a computer supported with software to control the image acquisition process and further processing, such as digitization, storage, modeling, and decision-making. All of these components contribute to the reliability of the hyperspectral imaging system and image quality. Therefore, an appropriate selection of system components is essential to ensure the proper performance of a hyperspectral imaging system and to acquire reliable, high-quality hyperspectral images. Both visible near-infrared (VNIR) hyperspectral imaging (400 to 1,000 nm) and near-infrared (NIR) hyperspectral imaging (900 to 1,700 nm) systems are currently used by researchers for different applications. The 400 to 1,000 nm range is industrially advantageous because of the wide availability and low cost of charge-coupled device sensors compared with the region between 900 and 1,700 nm (Gowen et al., 2009). The output of the hyperspectral imaging system is the three-dimensional (3-D) hypercube (x, y, λ). The 3-D data cube has 2 spatial dimensions (x, y) and 1 spectral dimension (λ). The hypercube $I(x, y, \lambda)$ can be viewed either as a gray level image $I(x, y)$ at each wavelength λ or as a spectrum $I(\lambda)$ at each pixel (x, y) as shown in Figure 2. Images at 2 adjacent bands are very similar in the hypercube, whereas images at distant bands can be much less similar and may have independent information. In addition, no single wavelength image has sufficient information to describe the object entirely, which explains why hyperspectral imaging is useful in analyzing an object (Elmasry et al., 2012).

Spectral analysis

Spectral analysis is the cornerstone of hyperspectral imaging investigation. The spectral bands in hyperspectral images are highly correlated. These high-dimensional data are sometimes redundant, noisy, and irrelevant or interfering. Appropriate analyses need to be conducted to extract meaningful information from such an enormous amount of data. Therefore, multivariate data analysis technique or chemometrics is required to extract meaningful information from the spectra to correlate with the target attributes to determine and visualize the distribution within the sample. The spectral data can be analyzed directly or following pretreatments, including baseline corrections, Savitzky–Golay filter for finding derivatives, normalization, and scaling (Cen and He, 2007). Among linear multivariate calibration techniques, partial least-squares regression (PLSR) has become the *de facto* standard in multivariate spectral analysis. It can handle highly colinear, noisy, and redundant data. PLSR aims to predict response variable(s) y from a (large) set of predictor variables X by reducing the set of predictor variables to a smaller set of uncorrelated latent variables (LVs). It then performs least-squares regression on these LVs, which are linear combinations of the original variables (predictors). That is the reason for the name "partial least-squares regression." These LVs are designed to capture the most information in X and y, and they have the best prediction power. Most of the adulteration detection applications using hyperspectral imaging in minced meat were modeled using PLSR. Although PLSR is very promising, unsatisfactory results can be obtained when nonlinearity is present between the spectral data and target attributes (Kamruzzaman et al., 2018). Therefore, nonlinear methods such as artificial neural network and support vector machine regression can be used to model nonlinearity (Nicolaï et al., 2007). Finally, an important aspect of developing calibration models is the correct reporting of calibration and prediction statistics to interpret the repeatability and accuracy. Generally, prediction statistics, including standard error of prediction (SEP) or root mean SEP and coefficient of determination (R^2), is more important.

Image analysis

Each pixel in a hyperspectral image has a spectrum; therefore, it is possible to calculate the level of adulteration at each pixel in the sample to generate chemical maps. However, it is practically impossible to measure the precise concentration of adulteration in every pixel of a sample. The regression models can be used to interpolate pixel-level calculations for all spots of the sample. This is executed by multiplying the spectrum of each pixel in the image and the regression coefficients obtained from the calibration model based on spectral data. The main steps for developing prediction maps are depicted in the flowchart shown in Figure 3. To speed up the adulteration map and reduce the time required for image processing, images at a few optimum wavelengths are usually used to create the adulteration map.

Results and discussion

Adulteration detection in minced lamb meat

As a promising nondestructive technology, hyperspectral imaging has been explored by Kamruzzaman

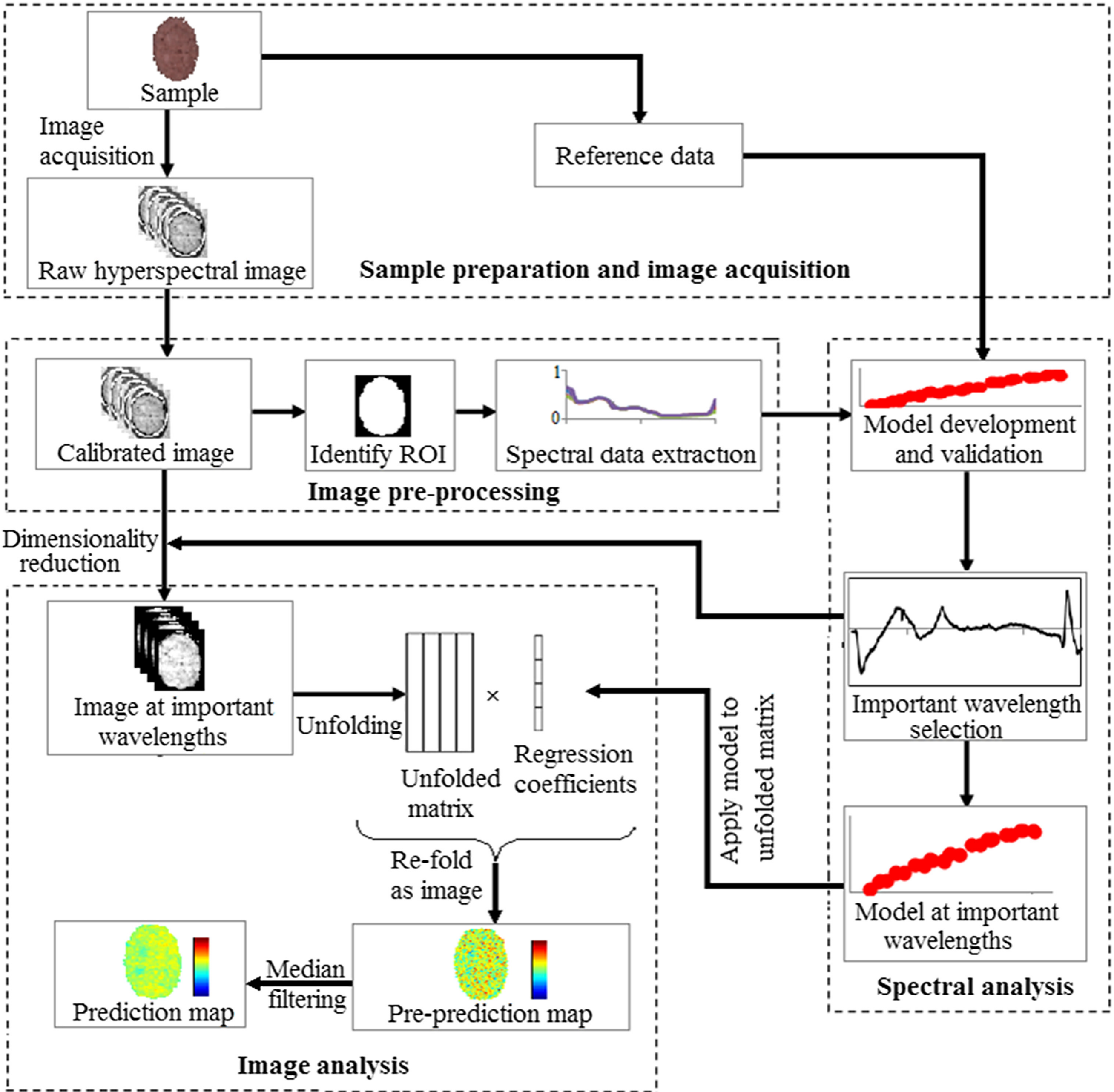

Figure 3. Flowchart for analyzing hyperspectral images for developing prediction maps (Kamruzzaman et al., 2013).

et al. (2012, 2013, 2015a, 2015b, 2016) for adulteration detection in minced meat. These applications will be briefly discussed in the following sections. For a detailed description, the readers are requested to see the original publications.

NIR hyperspectral imaging (90 to 1,700 nm) was tested to detect the level of adulteration in minced lamb meat (Kamruzzaman et al., 2013). To the best of our knowledge, this is the first reported study to detect adulteration in minced meat using hyperspectral imaging. Principal component analysis (PCA) was used to identify the most potential adulterate among pork, kidney, heart, and lung in minced lamb. Clearly, Figure 4 suggests that the most potential adulterate was pork, among others, because lamb and lamb mixed with pork clustered very closely. In reality, if the mixture of lamb and pork is predictable using this technique, then the mixture of lamb and offal would be predicted easily.

To detect the level of pork adulteration in minced lamb, the lamb samples were adulterated by mixing pork in the range of 2% to 40% at approximately 2% increments according to weight. The minced meat was put in a circular metal can and imaged using the

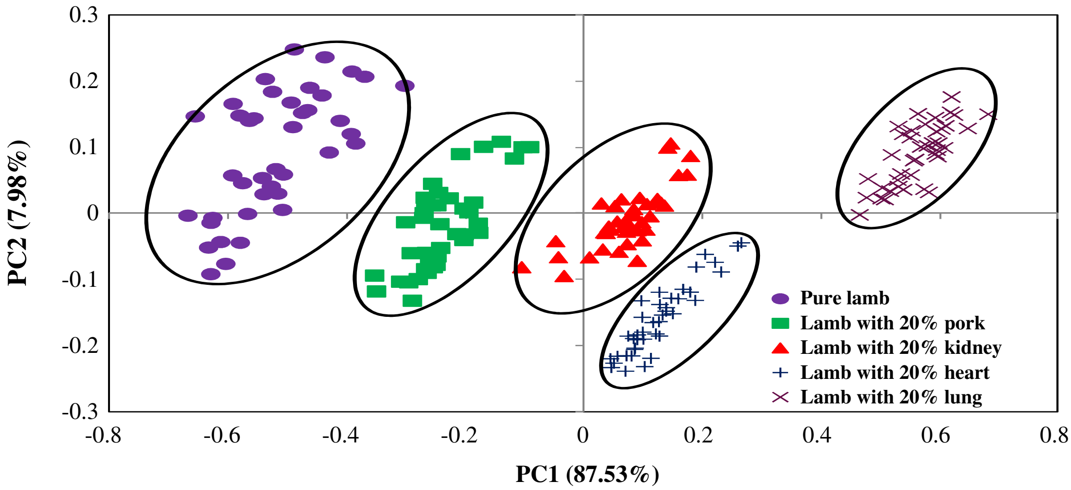

Figure 4. Principal component analysis scores plot for pure lamb and lamb mixed with 20% of different adulterates in the spectral range of 910 to 1,700 nm (Kamruzzaman et al., 2013).

hyperspectral system. PLSR was used to detect the level of pork adulteration in minced lamb with an R^2_{cv} of 0.99 and root mean standard error of cross-validation of 1.37%. The rate and extent of postmortem pH change influences the quality of meat and subsequently the spectral features. Therefore, it is necessary to evaluate the effect of pH on multivariate calibration for adulteration detection.

To develop a multispectral imaging system, 4 feature wavelengths centered at 940, 1,067, 1,144, and 1,217 nm were identified using regression coefficients. In addition, a multiple linear regression was developed and applied to each pixel in the image to obtain the distribution of adulteration of the tested samples. Although it was difficult to identify the level of adulteration with the naked eye, as shown in the RGB images in Figure 5, the prediction map revealed the change in adulteration from sample to sample. These results indicated that hyperspectral imaging technology is an effective and promising technique to detect adulteration in minced meat.

Adulteration detection in minced beef

A hyperspectral imaging system in the spectral range of 400 to 1,000 nm was used to detect the level

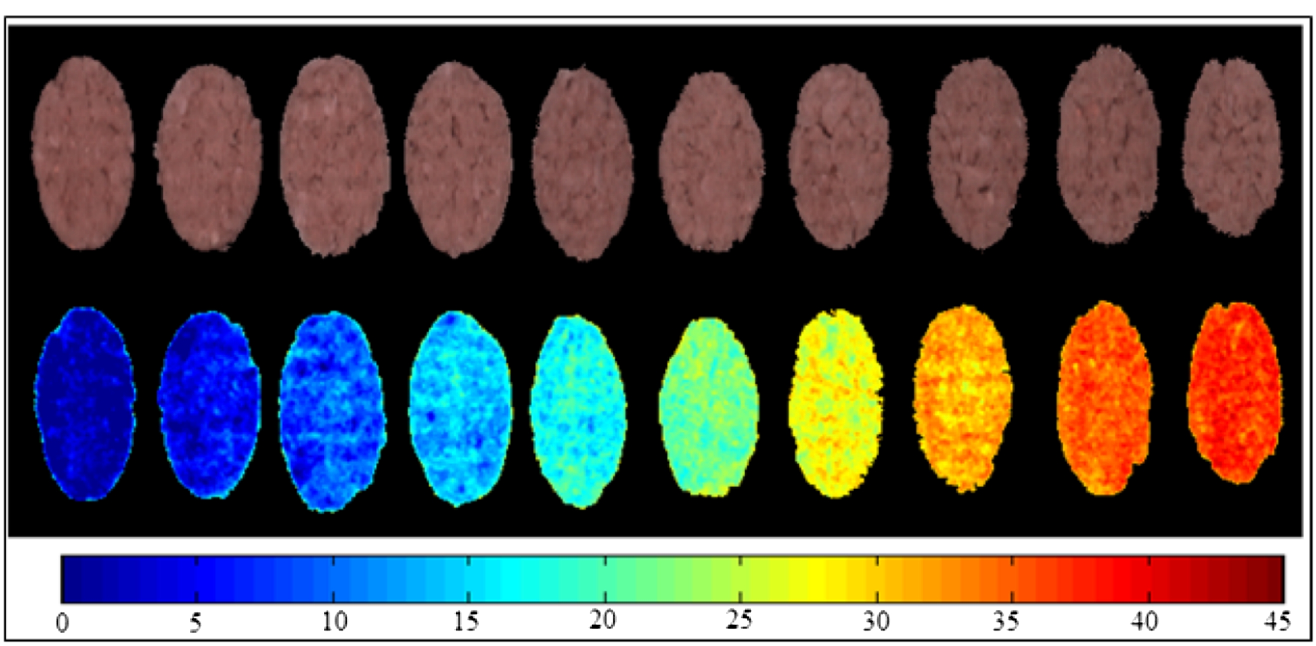

Figure 5. Application of near-infrared hyperspectral imaging for adulteration detection in minced lamb. RGB images (top) and corresponding prediction maps (bottom) of adulteration at different levels from 4% to 40% (left to right) with 4% increments (Kamruzzaman et al., 2013).

of horsemeat (Kamruzzaman et al., 2015b), pork (Kamruzzaman et al., 2015a), and chicken (Kamruzzaman et al., 2016) adulteration in minced beef. The minced beef samples were separately adulterated by mixing adulterants (horsemeat, chicken, and pork) in the range of 2% to 50% (w/w) at approximately 2% increments. Calibration models were developed using calibration samples and applied to independent validation samples. The performance of calibration models for predicting adulteration in minced beef using hyperspectral imaging is summarized in Table 1. The PLSR model was very effective in predicting adulteration in unknown samples, as indicated by the SEP and high value of R^2_p. Generally, 2 × SEP is considered as a 95% confidence interval in spectral analysis (Kelly et al., 2004). This means that the PLSR model cannot accurately predict samples below 4.46% (2 × 2.23), 8.88% (2 × 4.44), and 5.24% (2 × 2.62) adulteration in minced beef with horsemeat, chicken, and pork, respectively.

Some optimum wavelengths were selected to develop a simple model for visualization purposes, and the results are summarized in Table 2. Similar prediction results were obtained compared with the full spectral range, indicating that wavelength selection methods were effective for all cases. The optimized model was then transferred to each pixel of the image to create prediction maps or distribution maps. Figure 6 shows an example of prediction maps for horsemeat adulteration in minced beef with their corresponding RGB images. The results suggested that hyperspectral imaging could become a good way for rapid and nondestructive prediction of adulteration in minced meat in the spectral and spatial domain. However, it is vital to obtain a robust and precise calibration model for such prediction maps. Without a good calibration model, misleading prediction maps might be obtained.

Although all of the adulteration studies mentioned were performed with the same system using identical reference and data analysis methods, different feature wavelengths were selected to detect various adulterants (i.e., chicken, horse, and pork) in beef. According to these findings, different combinations of feature wavelengths must be used to develop a real-time multispectral imaging system to detect adulteration in minced beef. This is not a convenient situation for developing multispectral imaging systems to detect adulteration in one meat species. Therefore, it is desired to conduct a comprehensive study to establish a global calibration model to detect all possible adulterants in minced beef.

Many studies were carried out using spectral techniques (NIR spectroscopy and hyperspectral imaging) for adulteration detection in fresh minced meat (Kamruzzaman, 2016); however, only one study reported the use of NIR spectroscopy to detect adulteration in cooked meat. Alamprese et al. (2016) successfully used NIR spectroscopy combined with PLSR to detect turkey meat adulteration in cooked minced beef. Various ingredients and different technological treatments are needed to develop processed meat products. Various technological treatments along with different ingredients can mask possible interspecies adulteration. Because each pixel in hyperspectral has a spectrum, it is expected that hyperspectral imaging will be more promising than conventional spectroscopy to detect adulteration in cooked and processed meat.

Table 1. PLSR results for horsemeat, chicken, and pork adulteration in minced beef using VNIR hyperspectral imaging in the full spectral range

		Calibration		Prediction	
Application	LVs	R^2_c	SEC (%)	R^2p	SEP (%)
Horsemeat adulteration in minced beef	4	0.99	1.14	0.98	2.23
Chicken adulteration in minced beef	3	0.98	1.96	0.97	4.44
Pork adulteration in minced beef	6	0.97	2.54	0.97	2.62

LVs = latent variables; PLSR = partial least-squares regression; R^2_c = coefficient of determination in calibration; R^2_p = coefficient of determination in prediction; SEC = standard error of calibration; SEP = standard error of prediction; VNIR = visible near-infrared. Higher value of R^2 and lower value of SEC and SEP indicate very good prediction. It is always expected to obtain R^2 as close as 1 with errors (SEC and SEP) as close as 0.

Table 2. Statistics of different calibration models at selected wavelengths for predicting adulteration in minced beef

Selected wavelength (nm)	Pure species	Adulterate species	Multivariate analysis	Calibration statistics	Prediction statistics	References
515, 595, 650, 880	Beef	Horse	PLSR	R^2 = 0.99SEC = 1.21%	R^2 = 0.98SEP = 2.20%	Kamruzzaman et al. 2015b
430, 605, 665, 705	Beef	Pork	MLR	R^2 = 0.99SEC = 1.83%	R^2 = 0.99SEP = 4.17%	Kamruzzaman et al. 2015a
610, 665, 900, 980	Beef	Chicken	PLSR	R^2 = 0.97RMSEC = 2.27%	R^2 = 0.96RMSEP = 2.83%	Kamruzzaman et al. 2016

MLR = multiple linear regression; PLSR = partial least-squares regression; R^2 = coefficient of determination; RMSEC = root mean square error of calibration; RMSEP = root mean square error of prediction; SEC = standard error of calibration; SEP = standard error of prediction. Higher value of R^2 and lower value of SEC and SEP or RMSEC and RMSEP indicate very good prediction.

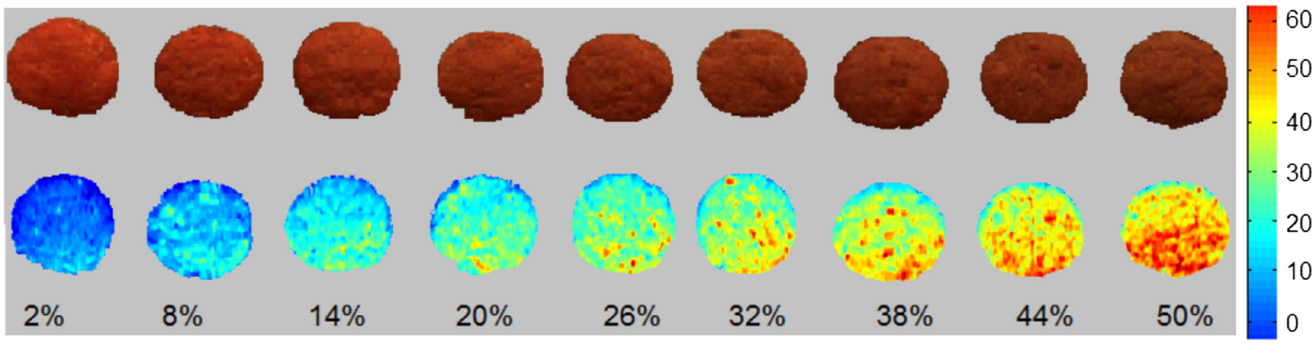

Figure 6. Application of visible near-infrared hyperspectral imaging for adulteration detection in minced beef. RGB images (top) and corresponding prediction maps (bottom) of horse adulteration in minced beef at different levels (Kamruzzaman et al., 2015b). The number below each sample is the percentage of horse meat in minced beef.

Authentication of red meat

Authentication of meat products is important for both consumers and industries. It is also important for accurate labeling to help consumers select appropriate types of meat products and for traceability because there are consumers who do not accept specific meat types in their diet for religious or ethical reasons (Rohman et al., 2011). For authentication of different red meat species, a hyperspectral imaging system was tested in the spectral range of 900 to 1,700 nm (Kamruzzaman et al., 2012). Six (957, 1,071, 1,121, 1,144, 1,368, and 1,394 nm) important wavelengths that give the highest discrimination among tested meat categories were first selected using the second derivative. Spectral data were then analyzed by PCA and partial least-squares discriminant analysis (PLS-DA) for recognition and authentication of the tested meat. The score plot of PC1 and PC2 (Figure 7) indicated that the tested meat classes could be easily distinguished into three separate classes. A PLS-DA model was then developed using these six wavelengths and achieved an overall accuracy of 97% in the calibration and more than 98% in the validation sets. Basically, it is straightforward to differentiate between pork, beef, and lamb muscles simply by visual inspection. On the other hand, minced meats are tough to authenticate because mincing visually removes the morphological structures of muscles. Therefore, the developed classification algorithms were then applied to both intact and minced meat in the independent testing set. Classification maps of the independent testing set and their corresponding RGB images are shown in Figure 8. RGB images of the

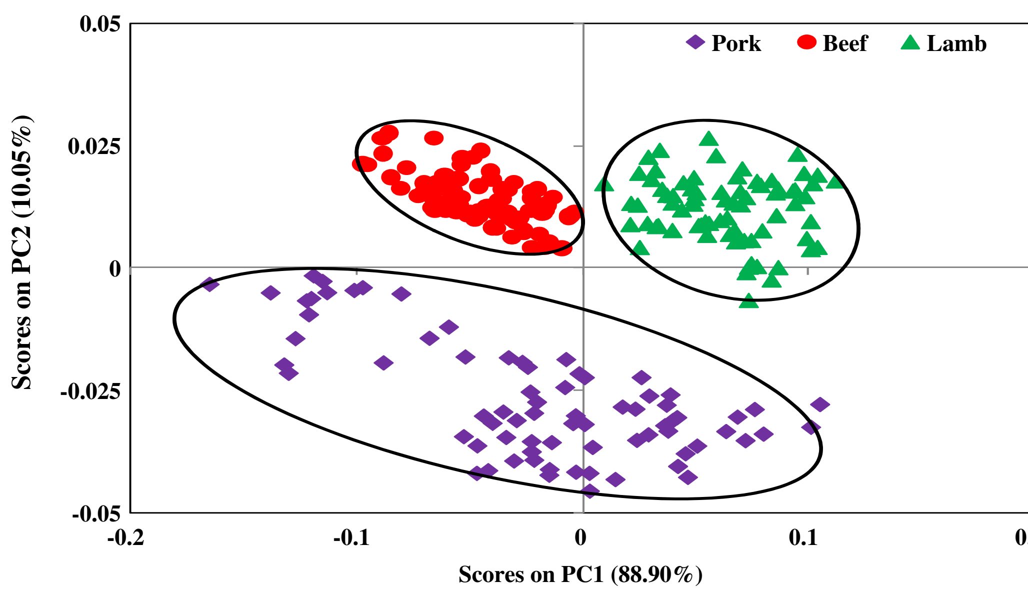

Figure 7. Principal component analysis scores plot of spectral data in the spectral range of 910 to 1,700 nm for red meat samples (Kamruzzaman et al., 2012).

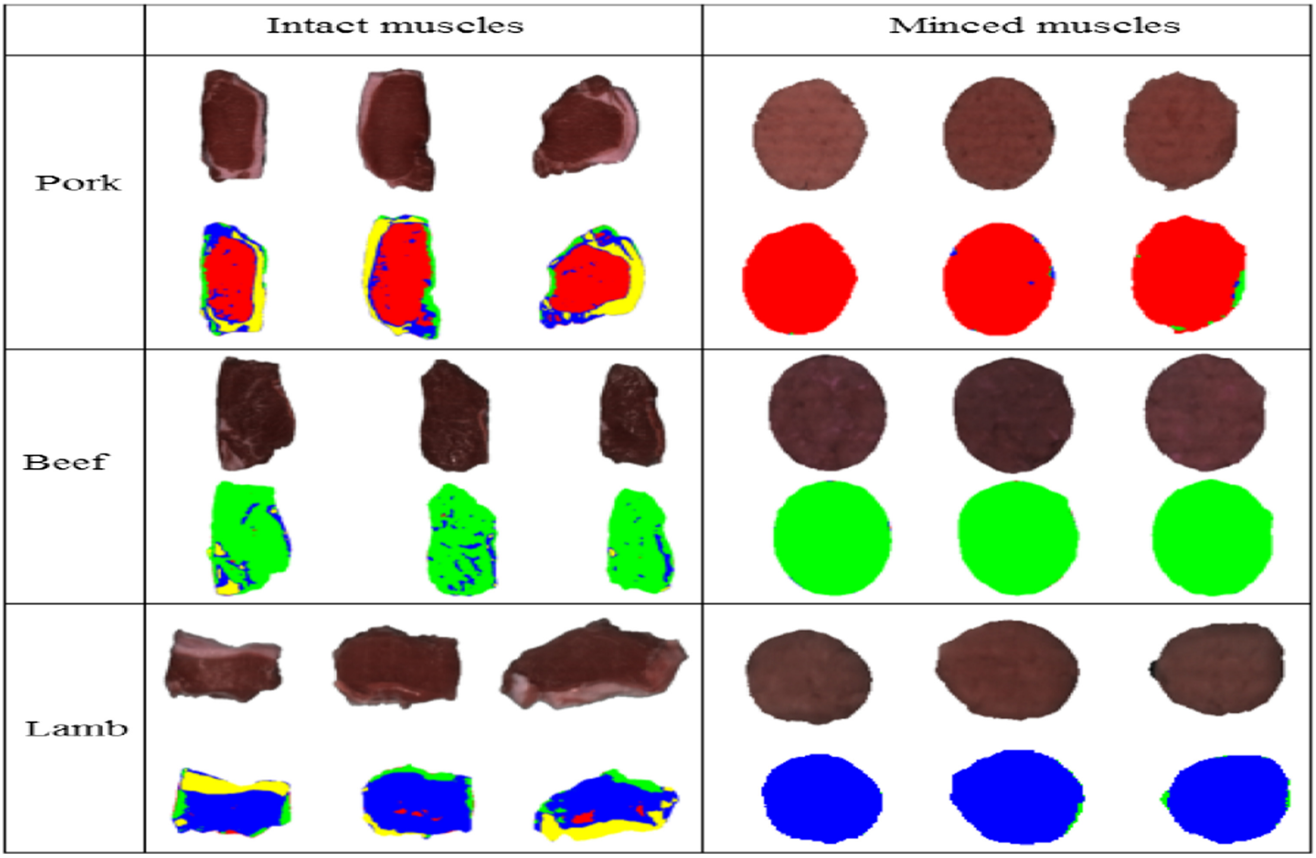

Figure 8. RGB images and corresponding classification maps of independent testing set containing both intact and minced meat samples (Kamruzzaman et al., 2012).

respective samples are shown for comparison and accentuate the difficulty of identifying each red meat by simple imaging method or visual inspection. The study showed that the calibration model developed with intact samples could be applied to minced meat to detect and quantify pork, beef, and lamb. This result indicates the potential of hyperspectral imaging for the authentication of different red meat species without referring to any sophisticated techniques.

Challenges and Future Perspectives

Hyperspectral imaging is an attractive option for authenticity and adulteration detection in meat. It has shown tremendous growth in the last decades due to advances in instruments and chemometrics. Despite many advantages, hyperspectral imaging has many intrinsic constraints limiting its widespread application in the industry. First of all, it is an indirect method based on accurate wet chemistry analysis. It requires a complex multivariate calibration. Therefore, it is crucial to know what types of multivariate data mining analyses are helpful for a particular application. Calibration transfer between instruments is also very critical for hyperspectral imaging applications. A calibration model developed on one device may not be useful for prediction on a second instrument. Therefore, calibration transfer is necessary. Calibration transfer from one instrument to another with statistically retained precision and accuracy is challenging (Cogdill et al., 2005). More effort and research are needed to transfer lab-based offline calibration into industrial-scale online settings. In hyperspectral imaging experiments, hundreds of variables can be measured simultaneously. Not all the variables contain important information, and these variables are redundant and highly correlated. Uninformative variables can lead to an unstable model. Therefore, effective variable selection is essential. Indeed, variable selection plays a vital role in any spectral tool for extracting critical information. Variable selection can improve the model interpretability with parsimonious representation, increase the model prediction ability, and speed up the prediction (Pu et al., 2015). It is anticipated that with only a few variables for a particular application and improved instrument hardware, the development of more robust and efficient algorithms will facilitate hyperspectral imaging for real-time inspection of authenticity and adulteration detection.

Conclusions

Whether intentional or accidental, food adulteration is a persistent global problem due to the complexity of fraudulent practices. Accidental adulteration could happen due to carelessness or lack of proper hygiene conditions of processing, handling, storing, transportation, and marketing. In contrast, intentional adulteration is commercial malpractice for financial gain, and it poses a significant concern in terms of health threats, quality, ethics, and religious views. The nondestructive, reagent-less, and multivariate characteristics of hyperspectral imaging techniques provide an exciting platform for adulteration detection and authenticity. Although very promising, hyperspectral imaging technology is currently suffering from 2 drawbacks: high cost and complexity. Therefore, the development of low-cost hyperspectral imaging instruments, improved processing speed, and progress in data analysis techniques will lead this technology to be a sustainable analytical tool. Commercial hyperspectral imaging systems have now started appearing on the market. The commercialization of hyperspectral imaging systems will boost the scope of applications in meat and other agro-food processing industries.

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