Received: 16 October 2020 | Revised: 29 March 2021 | Accepted: 11 May 2021

DOI: 10.1111/1541-4337.12781

COMPREHENSIVE REVIEWS IN FOOD SCIENCE AND FOOD SAFETY

Comprehensive REVIEWS in Food Science and Food Safety WILEY

Emerging nondestructive approaches for meat quality and safety evaluation—A review

Alfadhl Y. Khaled[1] | **Chadwick A. Parrish**[2] | **Akinbode Adedeji**[1]

[1] Department of Biosystems and Agricultural Engineering, University of Kentucky, Lexington, Kentucky, USA

[2] Department of Electrical and Computer Engineering, University of Kentucky, Lexington, Kentucky, USA

Correspondence
Akinbode Adedeji, Department of Biosystems and Agricultural Engineering, University of Kentucky, 128 C. E. Barnhart Building, Lexington, KY 40546, USA.
Email: akinbode.adedeji@uky.edu

Funding information
Kentucky Agricultural Experiment Station (KAES); National Institute of Food and Agriculture (NIFA), U.S. Department of Agriculture, Grant/Award Number: 1007893

Abstract

Meat is one of the most consumed agro-products because it contains proteins, minerals, and essential vitamins, all of which play critical roles in the human diet and health. Meat is a perishable food product because of its high moisture content, and as such there are concerns about its quality, stability, and safety. There are two widely used methods for monitoring meat quality attributes: subjective sensory evaluation and chemical/instrumentation tests. However, these methods are labor-intensive, time-consuming, and destructive. To overcome the shortfalls of these conventional approaches, several researchers have developed fast and nondestructive techniques. Recently, electronic nose (e-nose), computer vision (CV), spectroscopy, hyperspectral imaging (HSI), and multispectral imaging (MSI) technologies have been explored as nondestructive methods in meat quality and safety evaluation. However, most of the studies on the application of these novel technologies are still in the preliminary stages and are carried out in isolation, often without comprehensive information on the most suitable approach. This lack of cohesive information on the strength and shortcomings of each technique could impact their application and commercialization for the detection of important meat attributes such as pH, marbling, or microbial spoilage. Here, we provide a comprehensive review of recent nondestructive technologies (e-nose, CV, spectroscopy, HSI, and MSI), as well as their applications and limitations in the detection and evaluation of meat quality and safety issues, such as contamination, adulteration, and quality classification. A discussion is also included on the challenges and future outlooks of the respective technologies and their various applications.

KEYWORDS

computer vision, hyperspectral imaging system, meat quality, meat safety, multispectral imaging, nondestructive testing, spectroscopy

1 | INTRODUCTION

Meat is an essential component of the human diet, as it is a source of many nutrients vital to human health maintenance, the most important being proteins (Taheri-Garavand, Fatahi, Omid, et al., 2019). Meat is highly perishable due to its high moisture content and is therefore susceptible to rapid quality deterioration if not quickly and properly preserved. It is considered a breeding ground for microorganisms, which leads to food contamination and spoilage (Mewa et al., 2018; Shi et al., 2019). Guaranteed quality and safety of raw and processed meat has become a central focus in the meat industry as a result of an increasing number of recent safety issues and product recalls (Jia et al., 2018). Also, consumers are becoming more conscious of food labels and are paying closer attention to the quality of meat products (Kamruzzaman et al., 2016). These concerns are prompting the meat industry to begin to redefine and reevaluate standards for measuring and monitoring the quality and safety characteristics of meat and meat products (Grassi et al., 2018; López-Maestresalas et al., 2019).

1.1 | Meat quality evaluation

Meat quality evaluation can be defined as the determination of the characteristics used to assess the suitability of fresh or stored meat without any deterioration within a specified period (Taheri-Garavand, Fatahi, Omid, et al., 2019). Sensory attributes (color, flavor, and smell) are the consumer's initial impression of meat quality that directly affects purchasing decisions. Physical attributes include water holding capacity (WHC), marbling, and Warner–Bratzler shear force (WBSF) test results. Microbiological characteristics, such as total viable content (TVC) and bacterial contamination, are some of the most critical features in the quality and safety of meat. These can indicate the lack of or presence of disease or meat spoilage. Chemical attributes provide information on the composition and nutritional content of meat such as protein, moisture, and pH. All of these factors help to define the quality attributes of meat. Thus, from the viewpoint of meat quality and safety, reliable technology is required to monitor and determine meat characteristics before sale (Peng & Dhakal, 2015; Xiong et al., 2015).

Many well-established analytical methods have been applied to evaluate meat quality and safety. These methods are human sensory evaluation (HSE), chemical analysis, and instrumentation tests (Du et al., 2019). HSE involves the identification of meat quality manually based on some attributes including tenderness, flavor, and color. A benefit of HSE is that it provides immediate quality information (Sujiwo et al., 2019). However, this method is tedious, subjective, and depends strongly on the inspector's degree of fatigue and cannot assess the internal quality attributes of meat, such as pH level, moisture content, and presence of microorganisms (Limbo et al., 2009). On the other hand, chemical tests used in the detection of bacterial contamination in meat include enumeration methods such as microbial inspection/count (Song et al., 2012), serological tests such as enzyme-linked immunosorbent assay (Zvereva et al., 2015), and molecular tests such as polymerase chain reaction (Furutani et al., 2017). Instrumentation methods are applied to assess the texture or freshness of meat such as WBSF, a pH meter, and meat colorimeters (Bhat et al., 2019; Sujiwo et al., 2019). These methods (chemical analysis and instrumentation tests) are considered valid, consistent, precise, and reliable compared to subjective sensory evaluation (Peng & Dhakal, 2015). Nonetheless, there are many drawbacks to the application of these methods in meat quality detection as they are destructive, have complex sample preparation, require highly skilled operators, are unsuitable for on/in-line monitoring, and require long processing times (Khulal et al., 2017; Pophiwa et al., 2020; Wang et al., 2018a). The downsides of all three traditional methods highlight the need for more rapid, accurate, and nondestructive methods that can be used on meat and meat products for assessing the quality and safety, from animal breeding through consumption. For a modern meat processing facility, it is essential to have detection techniques that meet these needs, with as much ability to parallelize and automate as technological and economic limits will allow (Zhang et al., 2017).

In response to the above drawbacks, nondestructive techniques have gained much attention in recent years, and rapid advances have been seen. Scientists have developed various advanced techniques including electronic nose (e-nose) (Jia et al., 2018; Timsorn et al., 2016), computer vision (CV) (Bhargava & Bansal, 2020; Geronimo et al., 2019; Taheri-Garavand, Fatahi, Omid, et al., 2019), spectroscopy (de Nadai Bonin et al., 2020; Rady & Adedeji, 2018; Wang et al., 2018a), hyperspectral imaging (HSI) (Rady & Adedeji, 2020; Siripatrawan, 2018), and multispectral imaging (MSI) (Sendin et al., 2018; Su & Sun, 2018). These emerging techniques have merits above the conventional methods in that they can be nondestructive, rapid, and have the potential to be applied as an on-site detection method (Balage et al., 2015; Li et al., 2016; Velásquez et al., 2017).

These promising techniques have been extensively investigated to evaluate the quality and safety of different foods such as meat, fruits, and vegetables (Amodio et al., 2020; Bhargava & Bansal, 2020; Du et al., 2019; Fan et al., 2020; Lan et al., 2020; Mancini et al., 2020; Weng et al., 2020; Xu et al., 2019). Notably, in terms of applications in meat quality and safety assessment, these emerging approaches have been successfully applied to predict and detect sensory attributes (Peña-González et al., 2017), physical attributes (WHC) (Barbon et al., 2018), microbiological attributes (Khulal et al., 2016, 2017; Liu et al., 2020), chemical attributes (Geronimo et al., 2019), grading (Naganathan et al., 2016), muscle discrimination (Alaiz-Rodriguez & Parnell, 2020), contaminants, adulteration, and tumors (Rady & Adedeji, 2018, 2020; Xiong et al., 2015). This paper provides a comprehensive overview of current nondestructive techniques for evaluation of the safety and quality of meat and meat products. Also provided is a discussion focusing on challenges that must be addressed for industrial acceptance of these nondestructive methods.

1.2 | Search methodology

This study used specific keywords to search different databases for relevant literature. The full list of keyword combinations is as follows: ("meat quality" AND "e-nose"), ("meat quality" AND "CV"), ("meat quality" AND "spectroscopy"), ("meat quality" AND "HSI"), ("meat quality" AND "MSI"), ("meat safety" AND "e-nose"), ("meat safety" AND "CV"), ("meat safety" AND "spectroscopy"), ("meat safety" AND "HSI"), and ("meat safety" AND "MSI"). The pertinent records were retrieved from Web of Science, ScienceDirect, Springer, Wiley, Taylor & Francis Group, IEEE, MDPI, Hindawi, and Scopus from 2015 to 2020 without refining languages, countries, and types of articles. However, we retained all references older than 2015 that we believed will add valuable background material to the paper. In addition, bibliographies were searched for relevant records, and ProQuest and GoogleScholar were searched to ensure the comprehensive identification of relevant articles.

The studies found through these indexing strategies were separated into groups based on the emerging technologies being applied. The total number of studies indexed was 394, with 157 appearing in the final manuscript. Studies were removed from consideration in the final manuscript if their results were not promising, if they did not have justification for their methodologies, or if their work did not apply to meat inspection.

2 | TRADITIONAL MEAT QUALITY ASSESSMENT METHODS

Traditional methods of meat quality assessment include subjective and objective methods, namely, sensory evaluation and physicochemical techniques. These methods measure many different characteristics of meat, including sensory, toxicological, and nutritional content. The effectiveness and accuracy of these tests have been proven over time (over 90%). However, there are many disadvantages of the traditional methods, such as being destructive, the drudgery involved, long assessment time, the environmental impact of chemical waste, and the need for highly trained personnel for their operations.

2.1 | Human sensory evaluation

There are different detectable quality traits that consumers use to determine their desire when purchasing meat. The essential features that customers used to choose fresh meat are color, textural patterns, visual appearance, and odor. These parameters are related in one way or another to the physical and chemical properties such as marbling, protein content, and WHC. These detectable traits are useful and reliable indicators to determine the tenderness, toughness, or juiciness for cooked products. Many different markers are used for the determination of raw meat quality, including gender, species, and maturity level. The quality grade of a meat sample often relates to the part of the animal where it is cut from, the degree of marbling, color, firmness, and texture. These grades can sometimes be subjective, as they are evaluated by a human with an assumed level of expertise in the field.

Some studies where HSE for meat quality evaluation was applied are shown in Table 1. Generally, the results found in most of the previous studies did not correspond significantly to the chemical or microbiological changes of the meat. HSE generally considers only sensory criteria. Sometimes, when HSE is used to quantify microbiological characteristics, the error may be too large and result in a false positive, or false negative. HSE has a much wider confidence interval due to factors such as human error, which can cause significant problems. This example shows that HSE is not completely reliable and insufficient to give a deep insight into the quality of meat. For other reasons such as cost, time constraints, and subjectivity, HSE is not feasible or scalable for usage in a modern meat processing facility (Verplanken et al., 2017).

2.2 | Chemical and instrumentation methods

Chemical and instrumentation methods are well established in many sectors for the evaluation of food and agriculture products. However, some of them do not meet the basic requirement of speed and complexity required in modern food processing facilities. The destructive methods of chemical tests are only capable of sampling a minimal amount of tested products (Peng & Dhakal, 2015). Furthermore, chemical and instrumentation tests are expensive, both in labor and processing/reagents cost and they constitute a waste disposal problem. Often, they leave residues that constitute disposal problems.

There are currently many methods and tools applied to monitor and determine the quality and safety of different meat types (beef, pork, lamb, and chicken) such as WBSF (de Nadai Bonin et al., 2020), pH meter (Sahar et al., 2019), texture analyzer (Sujiwo et al., 2019), and HPLC

TABLE 1 Evaluation of meat quality and safety attributes using human sensory evaluation (HSE)

Meat type	Human sensory evaluation	Chemical and instrumentation evaluation	System evaluation	Significant results	Reference
Beef	Drip loss, off-odor, color, overall acceptability	pH, Color, Shear force, TVC	9-point hedonic scale: (1 = *lowest*; 9 = *highest*)	DMRT significantly different of means $p < .05$	Sujiwo et al., 2019
Chicken	Flavor, flexibility, apparent viscosity, color	ATP, IMP	5-point hedonic scale: (1 = *lowest*; 5 = *highest*)	HSE requires more practical experience	Lu et al., 2017
Fish	Appearance of skin, odor, outer slime and eyes	TVB-N, TMA-N	5-point hedonic scale: (1 = *lowest*; 5 = *highest*)	Tukey's significant difference test, $p < .05$	Parlapani et al., 2015
Beef	Aroma, drip loss, color, overall acceptability	APC	9-point hedonic scale: (1 = *extremely dislike*; 9 = *extremely like*)	DMRT significantly difference $p < .05$	Kim et al., 2018
Lamb	Flavor, texture, juiciness, overall liking	IMF	8-point hedonic scale: (1 = *extremely tough/dry*; 8 = *extremely tender/juicy*)	$R^2 = 10\%$ $R^2 = 8.6\%$ $R^2 = 5.7\%$ $R^2 = 11\%$	Lambe et al., 2017
Ham	Odor, taste, general quality	Boar taint prevalence	10-point hedonic scale: (0 = *not consumable*; 10 = *perfectly consumable*)	Accuracy 64%–80%	Verplanken et al., 2017

Abbreviations: APC, aerobic plate count; ATP, adenosine triphosphate; DMRT, Duncan multiple range test; IMF, intramuscular fat ; IMP, inosine monophosphate; TMA-N, trimethylamine nitrogen; TVB-N, total volatile base-nitrogen; TVC, total viable content.

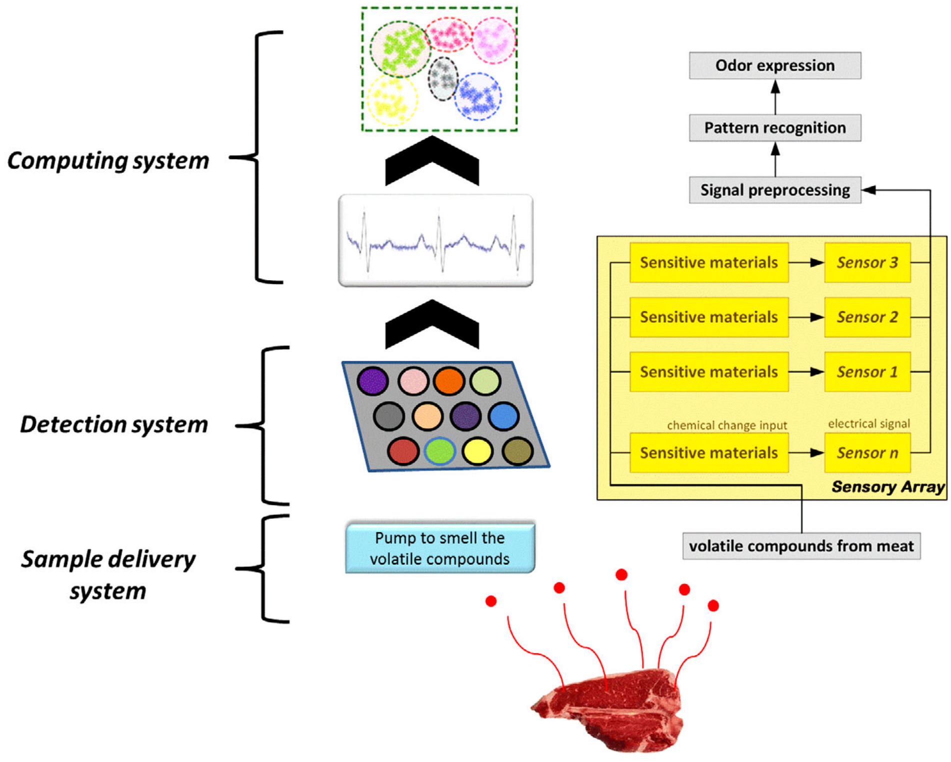

FIGURE 1 General illustration of e-nose system applied for meat quality detection

(Lu et al., 2017). As a whole, chemical and instrumentation tests are very precise and well standardized; however, due to their cost and drudgery associated with their use, they are not suitable for modern and adaptive, large-scale meat facility where high throughput and scale is required, and quick feedback is desired.

3 | RECENT ADVANCES IN MEAT QUALITY ASSESSMENT

The rapid growth in public awareness and concern for superior meat quality has increased the demand for the application of nondestructive techniques in evaluating meat quality and safety attributes. The need to reduce human contact with food and food product surfaces, especially in the wake of the COVID-19 pandemic, coupled with industrial trends in increasing the presence of automation and Artificial Intelligence (AI) in the food industry necessitates that many destructive test methods be replaced with rapid and equally reliable nondestructive techniques. From the literature reviewed, most advanced technologies based on imaging and the electromagnetic spectrum that are applied in evaluating meat quality fit the need criteria, namely, rapid, nondestructive, and suitable for on-line/in-line monitoring. In this section, the state-of-the-art of the following techniques is profiled: e-nose, CV, spectroscopy, HSI, and MSI. These technologies were chosen due to their ability to be scaled to industrial level, availability of hardware, and widespread ongoing research at the time of writing this manuscript (Jia et al., 2018; Lan et al., 2020).

3.1 | Electronic nose

E-nose (artificial olfactory sensing system) is a technique that simulates the human olfactory system (Edita et al., 2018). Generally, e-nose is an instrument applied to analyze food aroma and to identify volatile compounds. It is also capable of qualitative and/or quantitative analysis of simple or complex gases, vapors, or odors (Jia et al., 2018). E-nose consists of arrays of sensors that develop electrical signals in response to volatile compounds present in the gaseous sample (Timsorn et al., 2016). E-nose has typically three major systems: sample delivery, detection, and computing, as shown in Figure 1. The sample delivery system is used to enable the collection of a sample, which is then injected into the detection system. Practically, e-nose employs a pump to pull an air sample through a tube into a small chamber containing the electronic sensor array. The detection system includes a group of sensors to sense and react to the compounds, and the response is recorded by an electronic interface (Wojnowski et al., 2017). Next, collected signals are processed using an appropriate pattern recognition algorithm, followed by classification to label the unknown gas (Ramírez et al., 2018).

TABLE 2 Previous studies that report use of e-nose technique for meat quality and safety detection

Meat type	Quality attributes	E-nose type	Statistical approach	Significant results	Reference
Pork	TVB-N	Colorimetric sensor array	LDA, BP-ANN	97.5% and 100%	Li et al., 2014
Beef	Physicochemical indicators	PEN2	PCA, LDA, BPNN, SLDA, GRNN	96.19%	Hong et al., 2014
Tilapia	TVB-N	PEN3	PCA	–	Yan et al., 2015
Beef	TVB-N, red color, off-odor	PEN3	PCA, LDA, PLS	93%–99%	Sun et al., 2014
Ham	Sensory evaluations	PEN3	PCA	100%	Song et al., 2015
Pork	Color, moisture content, redox potential, pH	The Food Sniffer® (FS)	PCA	CP 1 (71.13%) and CP2 (12.57%)	Ramírez et al., 2018
Beef	Microbial component	Sensor array	kNN	93.64%, 86%, and 85.5%	Wijaya et al., 2017
Poultry	Odor	Sensor array	kNN, Classification tree, SVM, Naive Bayes (NB), Random forest	53%–79%	Wojnowski et al., 2017
Chicken	VFA	MOS system	–	$R^2 = .89$	Edita et al., 2018

Abbreviations: BP-ANN, back propagation artificial neural network; BPNN, back propagation neural network; GRNN, general regression neural network; kNN, k-nearest neighbors; LDA, linear discriminant analysis; MOS, metal oxide sensor; PCA, principal component analysis; NB, naive bayes; PLS, partial least squares; SLDA, supervised latent Dirichlet allocation; SVM, support vector machine; TVB-N, total volatile basic nitrogen; VFA, volatile fatty acids.

Generally, the odor of the sample stimulus generates a characteristic fingerprint that can be identified by several nonspecific sensors in the e-nose system. These fingerprints are compiled into a database, which is used to classify target scents (Jia et al., 2018). Typically, the signal analyses of e-nose data are complex and require the application of multivariate data analysis tools and specific pattern recognition methods to model signal response with chemical or physical reference parameters (Timsorn et al., 2016; Xu et al., 2019). Methods such as principal component regression (PCR), partial least squares (PLS), or artificial neural network (ANN) can be used to treat the complex e-nose data and extract relevant information.

E-nose has been established as a promising technique for meat freshness detection and it shows high potential in quality control and assurance. E-nose has many advantages, such as high sensitivity, fast result classification, the ability to detect hazardous or poisonous gases, and a wide range of operating conditions. Also, the e-nose has little to no special sample preparation and low per-sample cost (Gliszczyńska-Świgło & Chmielewski, 2017; Kiani et al., 2016; Sanaeifar et al., 2017). Nurjuliana et al. (2011) applied a zNose™ as an e-nose to evaluate pork quality based on a surface acoustic wave sensor. The authors found a two-dimensional olfactory image that successfully discriminates between samples qualitatively in a short time (15 s). Similarly, Song et al. (2015) used e-nose to investigate ham sensory evaluation. They found PCA model had the most effective extraction and the best precision in predicting sensory quality with R^2 of 1.0. Table 2 presents some findings of the application of e-nose on meat quality and safety detection.

The studies summarized in Table 2 demonstrated that e-nose technology has been successfully applied in meat quality detection and can be used as a promising technique to rapidly evaluate meat quality and safety, as well as to detect adulteration of meat. The e-nose techniques obtained satisfactory results of almost 90% average accuracy with the assistance of appropriate pattern recognition techniques for data analysis. These results allow us to conclude that it is possible to use the e-nose for meat quality and safety detection, and for the detection of harmful compounds. There are already several sets of pretrained e-nose databases, which are currently usable for industry applications. To be fully commercially viable, e-nose sensors must be made to last longer before deteriorating. The sensors currently on the market have a short life span, which needs to change before widespread usage can occur.

3.2 | Computer vision

CV is an emerging technology used for the detection and evaluation of external quality attributes in many

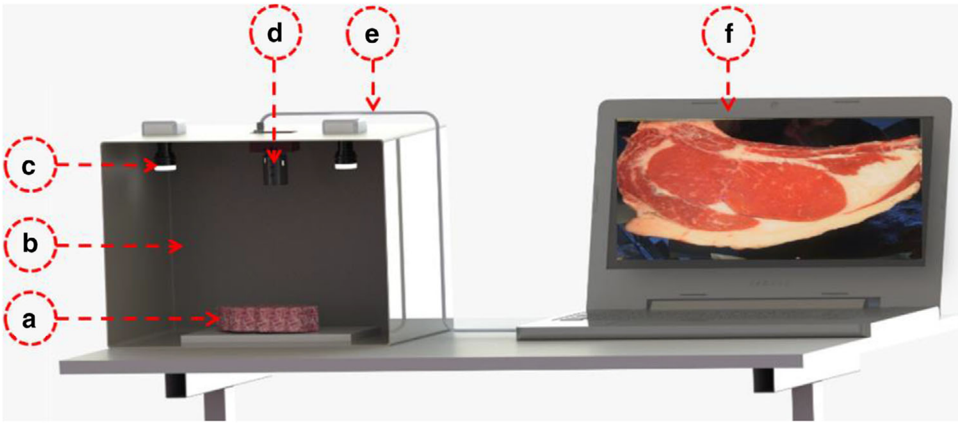

FIGURE 2 The overall system of CV system applied in meat quality detection, (a) sample, (b) lighting chamber, (c) light source, (d) CCD camera, (e) wire, and (f) computer

agricultural products (Barbin et al., 2016; Zhang et al., 2015). CV collects and analyzes spatial information gained from digital images of samples, such as color, size, and surface structure (Girolami et al., 2013). Currently, the applications of CV are mainly limited to surface detection. Generally, a CV system consists of a camera, a lighting chamber, a light source, a computer, and related software (Figure 2). CV has three different detection modes: reflectance, absorption, and transmission (Taheri-Garavand, Fatahi, Shahbazi, et al., 2019). Many factors determine the light's response in a measured object such as the wavelength and penetration of the incident light, the physical and chemical properties of the object, and the sample's refraction index (Barbin et al., 2016). Thus, having sufficient lighting on the object's surface can allow for better contrast and edge detection, which can aid the camera in surface feature detection.

CV data analysis is composed of two main parts: image processing and image analysis (scene/object recognition). In the investigated literatures, many different methods were applied to measure and analyze images by correlation, segmentation, identification of the regions of interest, feature extraction, and classification. These approaches include methods such as partial least squared regression, k-means clustering, stepwise multiple regression, support vector machine (SVM), linear discriminant analysis, ANN, and analysis of variance (Ruedt et al., 2020; Tomasevic et al., 2019).

CV techniques have proven their potential in the meat industry for the detection of surface quality characteristics and color classification (Peng & Dhakal, 2015), largely due to its nondestructive and flexible nature (Cubero et al., 2011). Zapotoczny et al. (2016) applied CV techniques to assess the quality of pork and poultry. The correlation between the image textures and chemical compositions was found to be in the range of .7–.92. In Table 3, many more studies are presented that show different ways of using CV to perform meat quality evaluation. These results indicate that CV can be used as a nondestructive tool to assess the quality and safety of meat in production lines; however, it needs significant refining of its ability to detect subtle color differences or texture differences that are equally important to the overall meat quality certification.

3.3 | Spectroscopy techniques

Spectroscopy is considered one of the most promising nondestructive techniques, due to its merit over many analytical approaches (Khaled et al., 2018). A typical spectroscopy system consists of four components: sampling devices, photodetector, light-isolating mechanisms, and a light source, as shown in Figure 3. In spectroscopy, there are three different data acquisition modes - interactance, reflectance, and transmittance. The relative locations of the detector and light source determine the mode. These modes have a direct influence on the wavelength passband, where the passband is narrow in transmission mode and is wide in reflectance mode.

Four different wavelength regions have been identified for meat applications: fluorescence, visible (VIS), near-infrared (NIR), and mid-infrared (MIR) regions. The American Society of Testing and Materials (ASTM) has quantified these different regions, where fluorescence wavelength range covers from 100 to 400 nm, VIS from 400 to 750 nm, NIR from 780 to 2500 nm, and MIR from 2500 to 25,000 nm (Fang & Ramasamy, 2015). These regions make up some of the different modes that a spectroscopic measurement device/procedure will operate in (Mancini et al., 2020).

TABLE 3 Previous studies on meat quality and safety detection using computer vision technique

Meat type	Quality attribute	Color space	Resolution (Pixels)	Statistical approach	Significant results	Reference
Pork	Color	RGB, HSV	5456 × 3632	Global thresholding, k-means clustering	$R^2 = .99$	Ruedt et al., 2020
Beef, pork, chicken	Color	L^*a^*,b^*	23.7 × 15.6 mm	ANOVA	$p < .05$	Tomasevic et al., 2019
Beef	Color	RGB, HSI	100 × 100	Fuzzy adaptive resonance theory map (ARTMAP), ANN	95.24%	Barbri, Halimi, & Rhofir, 2014
Pork	pH	CVS, CIEL$^*a^*b^*$	–	ANOVA	$p < .05$	Chmiel et al., 2016
Pork	Dry matter, protein, fat, ash, collagen content	RGB, $L^*a^*b^*$, XYZ, S, V, U	–	ANOVA	>89%	Zapotoczny et al., 2016
Pork	Color, marbling	HSI, $L^*a^*b^*$	–	SVM	92.5%, 75%	Sun, Young, et al., 2018
Chicken	Sorting	RGB, HSV	1280 × 1024	PLSR, LDA, ANN	93%	Teimouri et al., 2018
Pork	IMF	RGB, HSI, $L^*a^*b^*$	–	SVM	63%, 75%	Liu et al., 2018
Chicken	Freshness	RGB, HSI, $L^*a^*b^*$	3000 × 4000	CV, GA-ANN, ANN	$R^2 = .99$	Taheri-Garavand, Fatahi, Shahbazi, et al., 2019
Lamb	Marbling	RGB	–	MLP	91%	Przybylak et al., 2015
Chicken	Color	CIE $L^*a^*b^*$	3648 × 2376	CV colorimeter	$R^2 = .99$	Barbin et al., 2016

Abbreviations: ANN, artificial neural network; ANOVA, analysis of variance; CIE, Commission Internationale de l'Elcairage; CVs, computer visions; CVS, computer vision systems; GA-ANN, genetic algorithm–artificial neural network; HSI, hue, saturation, and intensity; HSV, hue, saturation, and value; IMF, intramuscular fat; L^*a^*,b^*, lightness, redness, and yellowness; LDA, linear discriminant analysis; MLP, multilayer perceptron; ARTMAP, adaptive resonance theory map; PLS, partial least squares; PLSR, partial least squares regression; RGB, red, green, and blue; SVM, support vector machine.

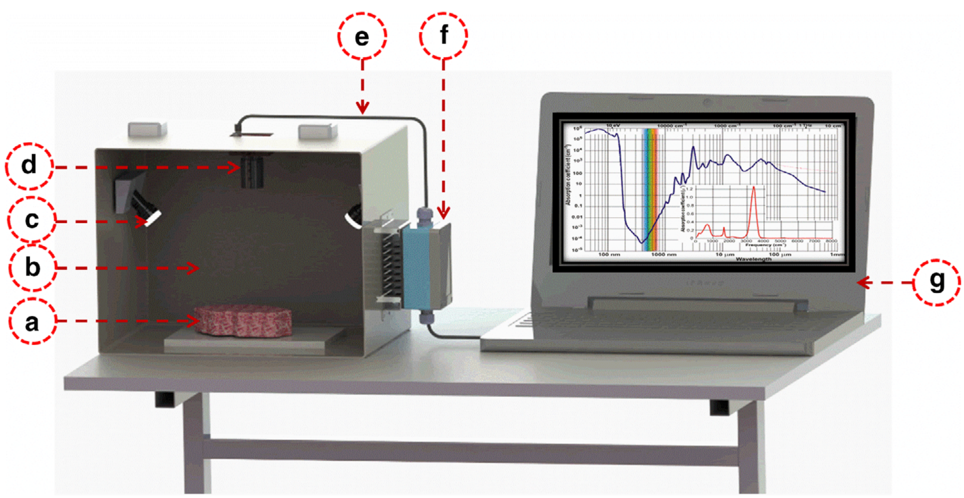

FIGURE 3 The general system of spectroscopy technique applied in meat quality detection, (a) sample, (b) lighting chamber, (c) light source, (d) spectrograph camera, (e) wire, (f) detector, and (g) computer

Spectral reflectance analyses have proven to be very useful in evaluating meat quality because changes in the absorption of incident light in the target regions of the electromagnetic spectrum defer based on the constituent of the region of interest. There are several published studies where spectroscopy was used for monitoring and detecting meat quality and microbial contaminations (Barbon et al., 2018; de Nadai Bonin et al., 2020; Savoia et al., 2020; Wang et al., 2018b). These quality attributes include shear force, TVC, IMF (intramuscular fat), TVB-N (total volatile basic nitrogen), and thiobarbituric acid-reactive substances in beef; TVC and TVB-N in pork; and drip loss, moisture, water activity, TVB-N, and adenosine triphosphate in poultry.

Overall, the reflectance properties of meat depend on the interaction of chemical constituents, fundamental vibrations, and stretching of molecules under exposure to electromagnetic radiation (Prieto et al., 2017). The variations of chemical constituents can form detailed fingerprints for quality detection, such as the freshness of meat (Prieto et al., 2009). The spectral information involved in VIS and NIR reflectance techniques indicates molecular vibrations of chemical constituents of meat, particularly the overtones and combination bands of vibrational modes in the form of C–X, where X is nitrogen, oxygen, or carbon and C is carbon. MIR spectroscopy can be divided into four wide regions: the X–H stretching region (2500–4000 nm), the triple bond region (4000–5000 nm), the double bond region (5000–6666 nm), and the fingerprint region (6666–25,000 nm). It has been reported that MIR absorbance derives from only one type of vibrational response and its spectral peaks are exclusive for a particular type of organic bond. Typically, the quantitative and qualitative analyses of spectroscopy data required in various analyses are computationally expensive, ill-fitting, and can be plagued by interference (Khaled et al., 2018). In addition, spectroscopy produces thousands of variables, so there must be careful consideration of how to deal with noise and informational redundancy. Methods such as MLR, PLS, and PCR can be used to preprocess the data and deal with these issues.

Some findings on the use of spectroscopy in meat quality and safety evaluation are shown in Table 4. In the reviewed studies, VIS, NIR, MIR, and fluorescence spectral regions were analyzed with a frequency of 60%, 80%, 8%, and 12%, respectively. The results display that VIS/NIR was applied by approximately three quarters of the reviewed studies, which can partially be explained by the speed, lower start-up cost, and lower complexity of the equipment. Fewer studies have reported on the applications of MIR and fluorescence spectroscopy for meat quality assessment. Some potential reasons for information in these areas include higher start-up costs and more complex equipment. Furthermore, spectroscopy techniques are in some ways a precursor to the techniques presented in Sections 3.4 and 3.5. As technology evolves, this led to HSI and MSI being used instead of just spectroscopy as a general trend. However, some recent studies still use spectroscopy techniques to show their advantages (see the case study in Section 4.1).

3.4 | HSI systems

HSI is a relatively new technique that is being applied to evaluate food product quality nondestructively (Kamruzzaman et al.,). HSI combines imaging and spectroscopy technologies for providing spatial and spectral information of the sample simultaneously. By this integration, HSI can detect the external and internal quality characteristics of a sample (Shi et al., 2019). In HSI, the spatial and spectral information allows the characterization and identification of a complex heterogeneous sample and a wide range of multi-constituent surface and subsurface features. Typically, an HSI system consists of a light source, a lens, an imaging spectrograph, a camera, a sample holding platform, and an interfaced computer with sample stage and data analysis software as illustrated in Figure 4.

HSI provides a large amount of information in three-dimensional hypercubes (x, y, λ), where x and y are spatial dimensions and λ is the spectral dimension. Hypercube data can be viewed in two ways: the entire spectrum at each pixel, or as a stack of images where each image represents a unique wavelength. There are three major methods for capturing a hyperspectral image: point-to-point scanning (whiskbroom imaging), where the spectra are collected pixel by pixel, line scanning (pushbroom imaging), where pixel spectra are acquired line by line, and area scanning (staring imaging) where the spectra are obtained by scanning all pixels at one wavelength, then repeating for each desired wavelength. The selection of which type to use will depend on the application, and the price, as the prices may vary widely.

Performing hypercube analysis can be challenging, as it may require applying chemometric modeling and statistical methods. Furthermore, classification and/or prediction models that are built using hypercube data will frequently need dimensionality reduction, as they can have large dimension and size (Cheng et al., 2017). There are many commonly applied techniques to preprocess data from a hypercube, such as interference correction, dimensionality reduction, and feature extraction (Oliveri et al., 2014). Spectral pretreatment techniques are used to reduce and correct interferences related to baseline drift, scattering, and overlapping bands, such as multiplicative scatter correction, smoothing, and baseline removal. Variable selection techniques are then applied to select the most informative spectral regions (the optimal wavelengths) for simplifying the model. These may include PCA, uninformative variable elimination, and genetic algorithms. Quantitative analyses are used to correlate, classify, predict, and validate the models such as MLR, ANN, and least square SVM. Figure 5 shows the flowchart of HSI, from image acquisition through the prediction model.

The application of HSI in the meat industry to evaluate quality and safety attributes can raise consumers' confidence in meat products, largely due to the ability to obtain specific information about each piece of meat when this was previously not feasible. Usage of HSI is helpful in the examination of chemical composition, adulteration,

TABLE 4 Previous studies on meat quality and safety detection using spectroscopy technique

Meat type	Quality attributes	Spectroscopy type	Wavelength range (nm)	Acquisition mode	Statistical approach	Significant results	Reference
Beef	pH, color, WHC, shear force	VIS and NIR	350–1649	Reflectance	ANOVA, Tukey–Kramer test	R^2_{CV} (.08–.78)	Savoia et al., 2020
Pork	Quality attributes	MIR	2500–14,285	Reflectance	Response correction, PLSR	–	Wang et al., 2018b
Chicken/poultry	Color, WHC, pH	NIR	968–2494	–	Decision Trees, SVM	77.2%	Barbon et al., 2018
Pork	Color, pH, TVB-N, fat, protein	VIS and NIR	400–2400	Reflectance	PLS	R_p = (.82–.95)	Wang et al., 2018a
Beef	Shear value, IMF	VIS and NIR	400–1395	Reflectance		100%	de Nadai Bonin et al., 2020
Minced beef and pork	Adulteration	VIS and NIR	400–1700	Reflectance	LDA, PLSR, SNV	96% and 100%	Rady & Adedeji, 2018, 2020
Beef	TVB-N, TBARS, TVC	Fluorescence	210–450	Reflectance	PLS	92.54% and 86.96%	Shi et al., 2020
Beef	pH, color, shear force	VIS and NIR	400–2498	Reflectance	PLS	R^2_{Cal} (.71–.81)	Prieto et al., 2014
Beef	pH, color, cook loss, drip loss	VIS and NIR	350–2500	Transmittance	PLS	R^2_{CV} (.91–.96)	Sahar et al., 2019
Pork	pH, color, WBSF	VIS and NIR	400–1395	Reflectance	PLS	R^2_{Cal} (.48–.88)	Balage et al., 2015
Beef, pork, lamb	Characterize meat, fat	NIR	750–2500	Transmittance	MSC, SNV, OSC, DOSC, OWAVEC	R^2_{CV} (.62–.96)	Prieto et al., 2017
Beef, pork, lamb, chicken	Meat freshness (VBN and TBA)	VIS and NIR	400–2500	Reflectance	ANN, PCA,	–	Kademi et al., 2019
Beef	Sensory, texture attributes	VIS and NIR	350–2500	Reflectance	PLS	R^2_{CV} (.22–.48)	Cafferky et al., 2020
Pork	Adulteration	MIR	5263–11,111	Transmittance	PLS-Kernel	REP = 3.7%	Abu-Ghoush et al., 2017
Beef	Fatty acid composition	Fluorescence	305–400	Reflectance	PLS	R^2_{CV} (.66)	Aït-Kaddour et al., 2016
Beef	WBSF, IMF	VIS and NIR	400–1395	Reflectance	PLS	100%	de Nadai Bonin et al., 2020
Lamb	IMF	NIR	900–1800	Transmittance	PLS	R^2 = .58, root mean squared error of prediction (RMSEP) = .85	Fowler et al., 2020
Pork	pH, drip loss, IMF	NIR and fluorescence	780–2500300-	Reflectance	PLS	R^2_{CV} (.06–.57) and (.04–.18)	Andersen et al., 2018
Lamb	Lipid oxidation	NIR	1400–2500	Reflectance	PLS-DA	R^2 = .69	Ripoll et al., 2018

Abbreviations: ANN, artificial neural network; DOSC, direct orthogonal signal correction; IMF, intramuscular fat; MSC, multiple scatter correction; NIR, near-infrared; OSC, orthogonal signal correction; OWAVEC, orthogonal wavelet correction; PCA, principal component analysis; SNV, standard normal variate; TBA, thiobarbituric acid; TBARS, thiobarbituric acid-reactive substances; TVB-N, total volatile basic nitrogen; TVC, total viable content; VBN, volatile basic nitrogen; RMSEP, root mean squared error of prediction; VIS, visible; WBSF, Warner–Bratzler shear force; WHC, water holding capacity.

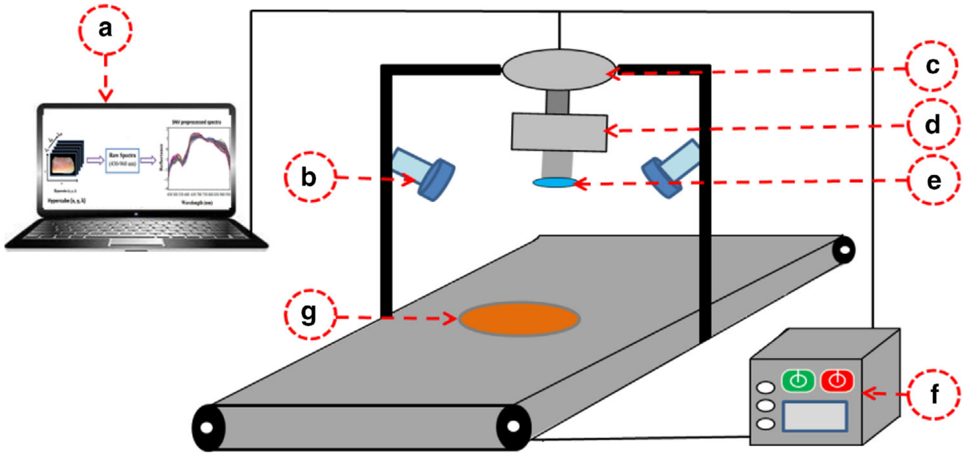

FIGURE 4 Schematic of an HSI system: (a) PC, (b) light source, (c) camera, (d) image spectrograph, (e) lens, (f) controller, and (g) sample

sensory attribute prediction, contaminant detection, and bacterial spoilage. Table 5 shows examples of many studies that have utilized HSI for the evaluation of different parameters in various types of meat (beef, pork, lamb, and chicken). These studies and their results reported that HSI combined with chemometric techniques has the potential for the rapid and nondestructive estimation of meat quality and safety characteristics. In the reviewed studies, HSI techniques have been shown to have accuracies ranging from 38% to 99%, with VIS/NIR with line scanning being the most frequently used approach. Despite the various advantages of this technique, it has some limitations with regard to direct implementation in an on-line system such as a lack of perfect accuracy (100%), which could portend high risk when dealing with food allergens or contaminants. If there can be a restriction in the number of captured/processed wavelengths, this will greatly reduce the amount of data, the amount of redundancy in the dataset, and the complexity of subsequent analysis and classification. Most industrial applications seek to select optimal wavelengths/features to ensure the quickest feedback from the multispectral model that ensues.

3.5 | Multispectral imaging

MSI is a promising and innovative technology that has been used in raw and processed meat inspection. MSI is considered a reformation of HSI, with the difference being that it takes an optimized subset of wavelengths used in HSI, such that it will operate on significantly less data (Ma et al., 2016; Sendin et al., 2018). Typically, MSI will use between three and 15 wavelengths, which are discrete, noncontiguous, and irregularly spaced (Feng et al., 2018). Having both a higher quality and lower quantity of information to process allows for MSI to achieve a more rapid identification and detection than line-scan HSI (Su & Sun, 2018). Using lesser wavelengths also allows for reductions in cost in the hardware and optical sensors as well (Sendin et al., 2018). Thus, if HSI and MSI met the same performance standards, MSI would be chosen for implementation for industrial systems. Just like HSI, MSI system captures three-dimensional images (a one-dimensional spectrum [λ] at every two-dimensional pixel [x and y]), which contain heterogeneous information reflecting meat physiochemical characteristics (Ma et al., 2016). Figure 6 shows an example of a typical MSI layout, where many different wavelength light sources are used to be able to capture spectral information simultaneously (Liu et al., 2016).

The main application of MSI in meat assessment has been quality and safety evaluation of products (Alshejari & Kodogiannis, 2017; Estelles-Lopez et al., 2017; Ropodi et al., 2018). Specific applications include frozen minced beef quality evaluation (Ropodi et al., 2018), heme and non-heme iron content prediction in pork sausage (Ma et al., 2016), and adulteration detection in chicken breast fillets (Spyrelli et al., 2021). In Table 6, many more studies are presented that show different ways of using MSI to perform meat quality evaluation.

4 | RECENT APPLICATIONS OF NONDESTRUCTIVE TECHNIQUES IN MEAT QUALITY AND SAFETY EVALUATION

4.1 | Meat microbiological spoilage detection

Meat is a highly perishable food and a fertile environment for bacterial growth due to its high moisture content (Huang et al., 2013). Thus, TVC of bacteria is considered

TABLE 5 Studies on meat quality and safety detection using the HSI technique

Meat type	Quality attributes	Wavelength range (nm)	Image size/resolution	Scanning mode	Statistical approach	Wavelength selection (nm)	Significant results	Reference
Pork	TVC	400–1100	1376 × 10402.8 nm	Line-scanning	MLR	506, 508, 547, 571, 575, 586, 490, 567, 587, 755, 766 479, 574, 580 [14]	R_v = .38–.94	Tao & Peng, 2014
Beef	TVC, *Pseudomonas* spp., and Brochothrix thermosphacta	405–970	1280 × 960 × 18	Point-scanning	PLS-DA	405, 450, 505, 570, 590, 660, 850, 870, 890, 970 [10]	.89–.91	Panagou et al., 2014
Mutton	TVB-N, TAC	400–1000	2.8 nm	Point-scanning	BPNN	–	94%	Xinhua et al., 2018
Pork	Water activity, pH, hardness, TBA	380–1000	5 nm	Line-scanning	DFA, QDI, PLS	–	R^2 = .96–.99	Siripatrawan, 2018
Beef	Tenderness	400–1000	1312 × 10820.16 mm	Line-scanning	PCA, FLD, SVM, DT	509, 541, 560, 577, 635, 739, 756, 910, 928, 972, 988 [11]	86.7%	Konda Naganathan et al., 2016
Pork	TVC, PPC	900–1700	320 × 450	Line-scanning	PLSR	964, 1128, 1151, 1301, 1341,1395, 1635 [7]	R^2 = .86–.89	Barbin, Elmasry, Sun, Allen, & Morsy, 2013
Chicken	TVB-N	430–960	200 × 200	–	SNV, ACO, PCA, BPANN	554, 638, 670, 726, 855 [5]	R_p = .88	Khulal et al., 2017
Pork	Fresh and frozen-thawed	400–1000	–	Line-scanning	PNN	400, 446, 477, 516, 592 686 [6]	93.14% and 90.91%	Pu et al., 2015
Poultry	TVB-N	430–960	1628 × 6182.73 nm	Line-scanning	PCA, ACO, BPANN	544, 638, 705, 726, 855 [5]	R = .75	Khulal et al., 2016
Beef	Marbling	400–1000	2.5 nm	Line-scanning	DT	440, 528 [2]	–	Velásquez et al., 2017
Chicken	Tenderness	400–1000	688 × 500	Line-scanning	PCA, PLS-DA	–	0.84(FR), 0.92(SR)	Jiang et al., 2018
Pork	pH	400–800	–	Line-scanning	SVR	404, 435, 546, 578, 750, 763, 772 [7]	0.93	Yao et al., 2019

Abbreviations: ACO, ant colony optimization; BPANN, back propagation artificial neural networks; BPNN, back propagation neural network; DFA, discriminant factor analysis; DT, decision tree; FLD, Fisher's linear discriminant; MLR, multiple linear regression; FR, full range; MLR, multiple linear regression; PCA, principal component analysis; PLS, partial least squares; PLS-DA, partial least squares-discriminant analysis; PLSR, partial least squares regression; QDI, quality deterioration index; R_p, correlation coefficient of prediction set; R_v, correlation coefficient; SMLR, sparse multinomial logistic regression; SVM, support vector machine; PNN, probabilistic neural network; PPC, psychrotrophic plate count; SMLR, stepwise multiple linear regression; SR, selected range; SVR, support vector regression; TAC, total aerobic plate count; TBA, thiobarbituric acid; TVB-N, total volatile basic nitrogen; TVC, total viable count.

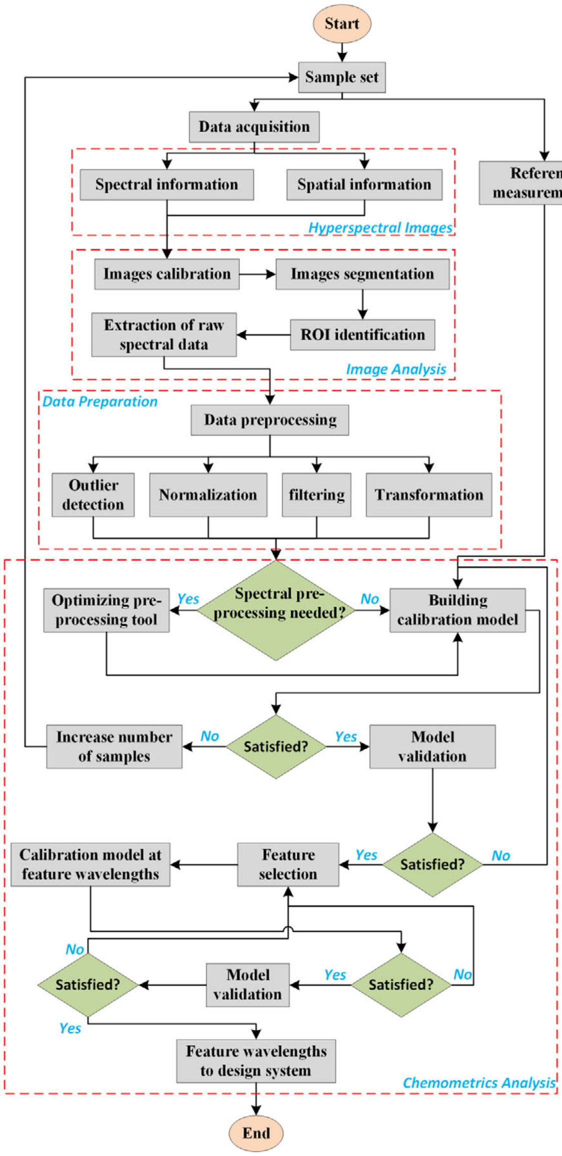

FIGURE 5 Flowchart of HSI technique for acquisition and to analyze data in meat quality and safety detection

one of the most important indicators that can be measured to perform the microbiological safety evaluation of meat (Parlapani et al., 2015). The international standards used in meat safety and quality assessment have set a threshold value of TVC; if it exceeds this threshold, the bacteria will become harmful to humans. Therefore, accurate knowledge of the TVC is crucial to protect consumers. Recently, advanced techniques have become a suitable alternative to the traditional methods used in meat industries. These advanced techniques include the use of nondestructive methods such as e-nose, CV, and spectroscopy to determine microbial spoilage in meat in a fast and precise manner (Feng & Sun, 2013; Huang et al., 2013). Specific applications of such techniques include e-nose, where Yan et al. (2015) and Wijaya et al. (2017) applied same to detect microbial counts and components in beef, as well as aerobic bacteria counts and TVC in pork. These studies had a cross-validation accuracy ranging from 87% to 100%. Additionally, spectroscopy and HSI techniques have been applied to determine TVC and Total Plate Count (TPC) in beef and pork (Khoshnoudi-Nia et al., 2018; Saricaoglu & Turhan, 2019; Tao & Peng, 2014). These approaches had an accuracy ranging from 80% to 100%. The variation in the results shown may be due to the difference in the technologies applied, as well as due to the surrounding environment. For example, temperature directly affects oxyhemoglobin formation, which plays a significant role in spoilage. Overall, these results show that these emerging technologies can be used to detect microbial spoilage, in a manner conducive to industrial use.

4.2 | Meat safety detection

Meat safety is an extremely important consideration for both meat producers and consumers. When selling meat, the producer must ensure that their products are safe and free from disease. Food production involves several different stages, including slaughter, processing, transportation, and distribution (Saucier, 2016). There are many different types of issues that need to be detected, including diseases, toxins, and deformities (Dasenaki & Thomaidis, 2017). HSI has been very promising thus far and has been investigated for its potential in identifying safety issues in meat. Kim et al. (2006) utilized HSI to detect tumors in chicken, with an accuracy of 98.2% using a PCA-based model. For differentiating healthy and systemically diseased fresh chickens, Chao et al. (2007) applied HSI. The system was able to detect 98% of healthy and 93% of systemically diseased chickens, using the selected feature wavelengths. Similarly, Nakariyakul and Casasent (2009) examined VIS- and NIR-based HSI to detect tumors in chicken. The authors selected eight optimal wavelengths and found an accuracy of 80%. Other studies have utilized HSI techniques to identify and isolate chicken skin tumors and found overall detection accuracies of 76%–98% (Barbin, Elmasry, Sun, & Allen, 2013; Chao et al., 2010; Feng & Sun, 2013; Tao et al., 2012; Wang et al., 2011). The impressive results that have been found from previous studies using the HSI system at VIS and NIR spectral ranges can be attributed to the difference of color pigments between tumor and meat, related to water bands such as 750 and 950 nm and to the

C–H, O–H, and N–H stretching vibrations.

4.3 | Meat quality classification

Meat quality classification is based on human perception, which can be based on physical and chemical attributes (Barbon et al., 2018). Chemical attributes include protein, pH, and IMF, whereas physical attributes include tenderness, juiciness, marbling content, and flavor. Accurate and precise meat quality evaluation is also pivotal for the meat industry, as it can determine better pricing if it has better classification. For example, pork can be classified into five grades: pale, soft, and exudative (PSE); radish, firm, and nonexudative (RFN); radish, soft, and exudative; pale, firm, and nonexudative; and dark, firm, and dry (DFD), where these grades are based on the combination of three main parameters (texture, color, and exudation) (Sujiwo et al., 2019; Taheri-Garavand, Fatahi, Omid, et al., 2019). As for beef quality classification, according to the United States Department of Agriculture (USDA), beef meat quality can be classified into three grades: prime, choice, and standard (USDA, 1997). These grades are based on the degree of both marbling and maturity.

HSI and spectroscopy are the techniques applied most often for nondestructive testing, with both based on the VIS and NIR regions of the electromagnetic spectrum (400–2500 nm). These wavelength ranges have advantages, including the ability to identify the biochemical composition of meat (water, protein, and fat content). For example, lights in the range of 950–1000 and 1350–1450 nm are bands synonymous to water. Also, light between 1100 and 1250 nm is related to C–H and N–H stretching vibrations, which help to detect some chemical attributes such as protein and fat. Pu et al. (2015) stated that wavelengths of 440, 470, and 635 nm are assigned to deoxymyoglobin, metmyoglobin, and sulfmyoglobin, respectively, which are related to the freshness and color of meat. Kamruzzaman et al. (2012) examined NIR HSI with wavelengths ranging from 890 to 1700 nm to classify pork, beef, and lamb muscle (longissimus dorsi). They found an overall correct classification rate of 98.67% for pork, beef, and lamb samples in the validation set using PLS-DA. A similar study was conducted by Barbin et al. (2012) to classify pork longissimus dorsi muscles into three quality grades (PSE, RFN, and DFD) using a NIR HSI system (900–1700 nm). Their overall correct classification rate was 97.44%. Together, these studies highlight that HSI, coupled with various classifiers, has the potential to be used as a fast technique to classify pork meat grades. Many studies applied HSI to classify lamb meat as well. For example, Sanz et al. (2016) used HSI to categorize four different lamb muscles (longissimus dorsi, psoas major, semimembranosus, and semitendinosus), and achieved a classification rate of 96.67% with Least mean squares (LMS). There is a breadth of material showing how these new technologies can be used to classify various meat types. This will undoubtedly prove useful in the future for both meat producers and consumers.

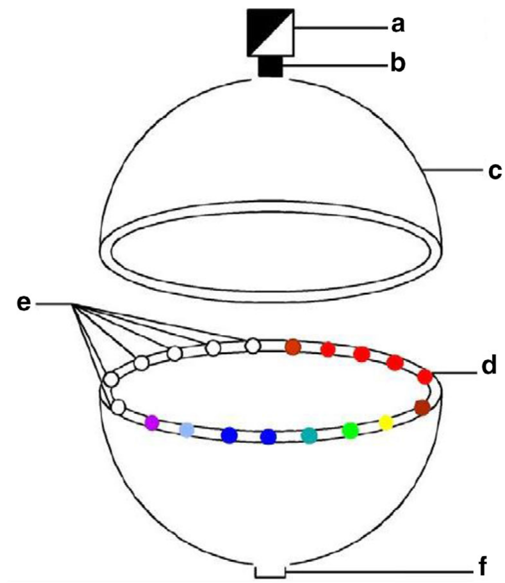

FIGURE 6 Principal setup of a multispectral imaging system (a) camera, (b) lens, (c) integrating sphere, (d) LEDs of multiple wavelengths, (e) NIR, and (f) sample is placed in target opening (Liu et al., 2016)

4.4 | Meat contamination detection

The supply chain of meat from its source to the consumer may predispose it to contamination by harmful substances. Meat contamination can either be internal (present before the animal is slaughtered) or external (present after slaughter, due to unclean surfaces or other factors) (Sanaeifar et al., 2017). Meat contamination leads to the appearance of signs of spoilage such as spots on the surface (white or green) or the changing of raw meat color from light pink/red to dark red/gray (Choi et al., 2020). These changes are due to the breakdown and damage of internal iron compounds. Thus, contaminated meat must be disposed of to prevent food poisoning and ensure that harmful substances (bleach, fecal matter) do not spread. The meat industry is facing the difficulty of identifying and separating contaminated meat from noncontaminated meat due to the high number of possible contaminants. HSE is the most commonly used inspection technique in the meat industry for contaminant detection. As previously stated, HSE has many limitations, including subjectivity, inconsistency, and inaccuracy. A better replacement will be

TABLE 6 Studies on meat quality and safety detection using the MSI technique

Meat type	Quality attributes	Spectral bands	Wavelength range (nm)	Statistical approach	Wavelength selection (nm)	Significant results	Reference
Pork	bone fragments	19	405–970	SPA, LDA, PCA–LDA, PLS-DA,	450, 470, 645, 660, 700, 780, 970	100% for test set	Wang et al., 2021
Beef	TVC	18	405–970	Neuro-fuzzy	405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 850, 870, 890, 910, 940, 970	94.64%	Alshejari & Kodogiannis, 2017
Beef	TVC	18	405–970	OLS-R, SL-R, PLS-R, PCR, SVR, RF, kNN	–	98.6%	Estelles-Lopez et al., 2017
Beef	Frozen-then-thawed	18	405–970	PLS-DA, SVM	–	100%	Ropodi et al., 2018
Beef, pork	Detect adulteration	18	405–970	PLS-DA, LDA	405, 430, 450, 470, 505, 565, 590, 630, 645, 660, 850, 870, 890, 910, 920, 940, 950, 970	98.48%, 96.97%	Ropodi et al., 2015)
Beef	Minced beef and horsemeat	18	405–970	PLS-DA, RF, SVM	–	100%, 96.62%	Ropodi et al., 2017
Beef	Water-injected	19	405–970	PLS-R	405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 780, 850, 870, 890, 910, 940, 970	94.6%	Liu et al., 2016
Chicken	TVC, *Pseudomonas* spp.	18	407-970	PLS-R, ANN	405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 850, 870, 890, 910, 940, 970	90.4%	Spyrelli et al., 2021

Abbreviations: ANN, artificial neural networks; kNN, k-nearest neighbors ; LDA, linear discriminant analysis; OLS-R, ordinary least squares regression; PCA–LDA, principal component analysis–linear discriminant analysis; PCR, principal component regression; PLS-DA, partial least squares discriminant analysis; PLS-R, partial least square regression; RF, random forest; SL-R, stepwise linear regression; SPA, successive projection algorithm; SVM, support vector machine; SVR, support vector regression; TVC, total viable counts.

nondestructive techniques to perform contaminant detection. For this application, spectroscopy and HSI look promising for industrial use.

Many studies have begun to examine meat contamination using emerging nondestructive techniques. Iqbal et al. (2013) examined e-nose to detect foodborne bacteria contamination on beef. HSI systems have also seen usage for contaminant detection, most often with poultry. For poultry contaminant detection, fecal matter and ingesta can introduce pathogenic microorganisms. However, in order for this detection method to properly work, the carcasses must be externally cleaned, as these contaminants are found internally. The current manual methods used recently have been having difficulty in detecting a small amount of fecal material in fast-moving carcasses with consistency. Yoon et al. (2011) highlighted that contaminated spots on the surface of poultry carcasses can be modeled by non-Gaussian properties and that the uncontaminated poultry carcasses could be modeled by a Gaussian distribution. In general, the detection of contaminants in meat depends on the difference in spectral bands between normal and contaminated skin/flesh. This difference in spectral bands and the proper multivariate models can lead to the development of an on-line system where contaminated meat can be identified in a quasi-real-time mode.

4.5 | Meat adulterant detection

Food fraud is a major concern for the food industry, especially adulterated meat. Spink and Moyer (2011) defined food fraud as an intended act of substitution or misrepresentation of food ingredients and/or food packaging. In recent times, the issue of commercial meat fraud has emerged, and its importance has increased with growing consumer awareness. Meat adulteration comes in several forms, such as inaccuracies in the species, gender, or quality (Johnson, 2014). For example, the horsemeat scandal in which beef was adulterated with horse by as much up to 100% in some cases (Premanandh, 2013). Also, minced meat is another common occurrence of adulteration, and it is important due to its usage in products such as meatballs, hamburgers, and sausages. Adulteration in minced meat can occur by substituting inexpensive meat or proteins from animal or vegetable origin (Kamruzzaman et al., 2013). Through traditional evaluation methods, it is difficult to determine and identify meat types used due to removing the morphological structure of meat and the similarity of authentic and adulterated products. Adulteration detection has become fundamental in the meat industry for accurate labeling and to meet the consumers' standards. Many of these international standards come from religious, medical, ethical, or dietary concerns (Boyaci et al., 2014).

Thus far, previous studies have used emerging techniques such as spectroscopy and HSI to detect adulteration in meat. Alamprese, Casale, Sinelli, Lanteri, and Casiraghi (2013) applied spectroscopy to study minced beef adulterated with turkey, and achieved an accuracy rate of 98.3%. Also, Barbin, Elmasry, Sun, Allen, and Morsy (2013) achieved a classification rate of 94%, 95%, and 97% for fresh and frozen-thawed minced beef adulterated with beef offal, beef fat, and pork, respectively. Rady and Adedeji (2018) investigated the application of spectroscopy at two ranges including VIS/NIR and NIR to evaluate adulterant minced beef and pork. The authors found a classification rate of 69%–100%. The same authors extended their study with the application of HSI and machine learning methods to identify adulteration in minced beef and pork. The optimal classification models based on selected wavelengths of the test set achieved classification rates of 75%–100% for pure samples and 100% for adulterated samples (Rady & Adedeji, 2020). Kamruzzaman et al. (2013) applied NIR HSI to detect the level of adulteration in minced lamb meat. They found R^2cv of .98 was achieved using the optimally selected wavelengths. The successful application of spectroscopy and HSI in detecting meat adulteration is due to the differences in the amount of light absorbance/reflectance for different meats and adulterants. The bands related to the C–H, O–H, and N–H stretching vibrations in the NIR region were most likely influenced by the adulterant material. Moreover, the VIS region can detect the adulterant material due to the changes of water and myoglobin proteins, with the bands (around 440, 475, and 550 nm) related to deoxymyoglobin, sulfmyoglobin, and oxymyoglobin.

4.6 | Meat bone fragments detection

Bone fragments are small, often sharp parts in meat. The presence of bone fragments can either be due to broken bones inside the carcass before slaughtering or unbalanced cutting blades that shaved pieces from the skeleton. In general, the presence of bone fragments in boneless meat has risks for both producers and consumers. Consumers expect their meat to be free of any pollutants that threaten their safety and the presence of bone fragments may cause risks to them. On the other hand, producers can lose a lot of money due to the presence of bone fragments in their products, insurance claims and legal fees, as well as the loss of consumer trust. Therefore, it is necessary to detect and remove bone fragments from meat products before sale. Currently, the detection of bone fragments is a significant challenge, and the use of traditional manual inspection is difficult. Thus, the described emerging technologies are promising to solve this problem. Lim et al. (2020) applied HSI with wavelengths ranging from 987 to 1701 nm to detect bone fragments in beef, pork, and chicken. The authors reported a 93.3% accuracy for most bone fragments detection using an image subtraction algorithm. Their findings were promising and demonstrate the effectiveness of HSI when combined with appropriate image processing models for bone fragment detection.

5 | CHALLENGES AND FUTURE DIRECTION

In general, the emerging nondestructive approaches (e-nose, CV, spectroscopy, HSI, and MSI) have proven their potential in nondestructive meat quality assessment and safety inspection. Most of the previous studies reported promising results with accuracy rates higher than 80%. The results of these studies show that these technologies have useful scientific potential, as well as a strong need for development in their ability for industrial usage (or potentially usage by everyday people). To overcome this shortfall, researchers must address the capability of their research to scale to an industrial level, such that the development of these technologies serves a purpose beyond its potential at the laboratory scale. Computing speed, scanning time, and distance needed from the sensor to the object are some important parameters for optical systems, as these would greatly define the development of real-time automated processing systems. Examples of other challenges that must be overcome include auto-adaptation/correction for poor lighting conditions, studying the effects of various types of noise, reducing the cost of sensors/data acquisition hardware, and reducing the amount of data from these technologies that must be processed, such that automated decisions can be made in real time. A specific example of this is that lighting can be a limiting factor for the precision of optical methods, and the wavelengths of light from existing light sources could greatly affect the accuracy and precision of an optical system. Khaled et al. (2018) stated that the signal-to-noise ratio could fall due to interference from noise or random interruptions (e.g., a light switching to off/on mode for optical applications, or a nearby chemical spill/contaminant for e-nose).

To overcome these issues, many solutions can be researched and implemented in the area of hardware and software. Hardware improvements may include size reduction (to fit in an on-line setting), new sensor types (longer e-nose lifetime), innovative environmental suppression procedures (optical filtering glass, sound absorptive materials), and new network integrations that are faster and more reliable over a longer period. Software solutions include new algorithm models for optimal wavelength selection, multispectral model implementation, and higher computing efficiency (HSI, spectroscopy, CV), all of which can enable faster on-line detection with acceptable accuracy, rapid feedback, and improved resistance to outside noise/interference. Another major improvement is to use sensor fusion. Utilizing many different technologies at once can capture a significantly wider variety of information in a short time, which can improve both the accuracy and reliability of designed systems. Some researchers investigated sensor fusion combinations such as HSI and CV to predict minced pork (Barbin, Elmasry, Sun, & Allen, 2013), and NIR spectroscopy, CV, and e-nose to evaluate meat freshness (Huang et al., 2015). These studies reported that fusing data from more than one technique led to better results than one single approach due to the ability to leverage nonredundant information collected from multiple systems to provide more accurate and precise evaluations. Another example is where colorimetric sensor array and optoelectronic nose were used to assess the quality and safety of meat on a production line (Li et al., 2018; Xiao-wei et al., 2018). These authors believe that the exact physical mechanisms of the response between the quality attributes and spectra/sensor arrays are still unclear in the current literature, which warrants for researchers to further investigate this area as developments continue to bring these technologies closer to industrial use. Knowledge of the underlying physical response mechanisms would be a great asset to confidence in the industrial adaption of these technologies for commercial purposes.

Another avenue that would be beneficial for researchers to pursue is improving meat quality control during the different steps of the supply chain such as transportation, storage, and packaging. Fluctuating environmental conditions such as high temperature or changing humidity can negatively impact meat quality and its shelf life. Del Olmo et al. (2014) reported that modified atmosphere packaging and high-pressure processing in pork products can influence pH and microorganism activity, which then changes the pork's flavor. Säde et al. (2013) discovered a new type of enterobacteria that can grow in meat and poultry samples at the modified atmosphere packaging. To prevent these changes, there must be careful real-time monitoring of the packaging conditions for all meat, such that there will be no risk of microbial spoilage during storage or transport. These issues present an urgent requirement for technology that can monitor and control the quality of meat products during storage and transportation. A strong candidate for this is the Internet of things (IoT). IoT is a highly promising family of technologies that is capable of many solutions to the modernization of agriculture for food security. IoT can result in a variety of sensor designs (such as those based

TABLE 7 Comparison of advanced techniques in meat quality and safety detection

Techniques	Accuracy conditions	Applicability for rapid detection	Applicability for industrial setting	Speed of detection	Advantages	Limitations
E-nose	A stronger odor detection, and provides high accuracy.	E-nose has limitations for rapid detection due to the chemical reactions in different sensor arrays.	Because it is not as rapid, it is challenging to apply in the meat industry.	This technique takes several minutes.	Cause no loss of aroma. Good for detecting odor and flavor compounds. It can be versatile and is easy to train on new instruments.	It has high fabrication costs. It requires a large computation time. It is easily affected by environmental conditions, which cause sensor drift.
Computer vision	Accuracy depends on the environmental conditions such as the surrounding light and on the type of camera.	The technique shows the potential for rapid detection if combined with the proper software.	Moderately difficult, depending on the quality of the camera used.	The speed can greatly vary, depending on the camera/image size and processing power of the computer and software.	Rapid and objective. Reliable and consistent. Providing spatial information.Able to detect external attributes.	Artificial lighting is needed. Requires regular calibration. Limited multi-constituent information inspection.Unable to detect internal attributes.
Spectroscopy	Accuracy depends on the features of the detector such as electrodes, probes, or cameras and the physical structure of the sample.	Detection is rapid.	Pure spectroscopy can be hard to use in an industrial setting, due to noise issues, but the quality of the sensors plays a large part in how difficult it can be.	Some time is required for setup. Scanning time is usually quick. Processing time largely varies based on computer type and processing software.	Provide high resolution of spectra. Able to detect internal attributes. It is can be rapid.	Limited sensitivity to minor components. Limited by background conditions and lighting present.

(Continues)

TABLE 7 (Continued)

Techniques	Accuracy conditions	Applicability for rapid detection	Applicability for industrial setting	Speed of detection	Advantages	Limitations
Hyperspectral imaging system	Provides high accuracy because it utilizes the spectral and spatial information of the object.	The technique shows the potential for rapid meat quality detection and safety evaluation.	HSI has great potential to be applied in the industrial setting for online/inline meat quality assessment and safety assurance.	Currently, the detection speed of an HSI system can be as quick as tens of microseconds. Factors such as the number of wavelengths considered and the systems processing power will greatly affect this.	Provides spectral and spatial information. Able to detect some internal and external attributes.Rapid and objective.	Sensitive to the environmental condition. High cost. Complex data processing.Hardware complexity.
Multispectral imaging system	Similar to HSI of providing high accuracy due to the combination of the special and spectral information of the data.	MSI illustrates the high speed for meat quality detection due to the selection of the usable bands.	MSI has great potential to be utilized in the industrial application due to the few wavelengths needed when compared to HSI. This results in it having faster computation time, and less mem-ory/computational resources needed.	MSI has very high detection speed, with it being as fast or faster than HSI in both acquisition and processing.	Provides spectral and spatial information. Able to detect some internal and external attributes. Potential for even shorter processing times	Hardware complexity. Sensitive to the environmental condition. High cost.Complex data processing.

on HSI) that are suitable for real-time monitoring, evaluating, and identifying meat quality and safety attributes including pathogens, carbon dioxide, oxygen, and/or temperature and provides real-time data for effective action implementation that reduces risk and cost (Shenoy, 2016).

The recent coronavirus pandemic presents a dire need to add automation to industrial meat processing to ensure production continues even with limited floor workers. Hart et al. (2020) described a situation originating in a Smithfield processing plant in Sioux Falls, South Dakota (USA), where more than 300 plant workers tested positive for COVID-19 in April 2020 and the plant was closed, which led to a severe hike in meat products price due to the disruption in production. This problem highlights an urgent need to develop nondestructive testing methods that will reduce human contact during food production. The foundation technology for automation and AI in the food industry are smart sensing systems that can assess food quality and perform the same function done by humans. Many of the described nondestructive techniques should be developed so that they can become part of the foundation of automated food quality assessment in the food industry.

Another technology that has great promise in the modern meat industry is portable and handheld optical devices. These systems should allow for quick and easy spot checking and could be of great value during several stages of production and sale of meat products. However, the development of such devices has been very limited due to factors such as low camera quality (when compared to industrial cameras) and poor usage conditions (lack of dexterity in the use of the device often impacts accuracy) (Kademi et al., 2019; Kiani et al., 2016; Yao et al., 2019). In the case of e-nose, the application challenges include a shot life span of sensors, and also the type and detection accuracy of the sensor array. For this reason, the materials used for e-nose sensors should have a very high sensitivity to the samples being detected. Another challenge is the lack of miniaturization of the e-nose sensing system. This should be achieved to develop novel portable devices with reduced integrated sensors to enhance detection limit, sensitivity, and working range, as well as minimizing costs and simplifying analyses. Similarly, the development of mobile phone applications based on CV will be desired to allow consumers to evaluate the quality and safety of meat. The innovation of both technologies will be promising to watch, as there has not been enough work done to fully realize the ideas. As shown in this section, there are many possibilities that researchers can pursue to aid in the modernization and improvement process of the meat industry. All of these applications have significant benefits to both producers and consumers and have enough merit to warrant future work. The overall comparisons of five primary nondestructive techniques are summarized in Table 7.

6 | CONCLUSION

In this paper, we presented a comprehensive review of the conventional and nondestructive methods for evaluating the quality and safety of meat and meat products, highlighting the limitations of the conventional methods and the need for better solutions that are adapted for current industrial use. We summarized five emerging nondestructive techniques that have been used for meat quality and safety detection, namely, (i) e-nose, (ii) CV, (iii) spectroscopy, (iv) HSI, and (v) MSI. Among the methods reviewed, HSI shows great merits over the others based on the degree of accuracy, versatility, and wide range of applications it can be used for in meat quality and safety assessment. However, its applications are still mostly at the laboratory scale and are not fully developed yet for an on-line industrial application. Similarly, the applications of e-nose are very promising for this industry but are much less developed than optical methods. The requirements for chemical and signal processing, along with the device limitations, restrict the scaling and proliferation of these technologies for the time being. The need for automated nondestructive detection systems is highlighted due to the experience forced on us by COVID-19 and other possible future public health outbreaks. In conclusion, these techniques are shown to have the potential for applications on meat as nondestructive quality and safety detection tools. Despite current limitations, there are still a wide breadth of possible improvements and research to be done, which would allow for successful commercialization, especially the HSI- and MSI-based systems. Thus, future studies should focus on enhancing the accuracy, scalability, robustness, and simplicity of these technologies, especially for industrial applications.

ACKNOWLEDGMENTS

This work was supported by the Kentucky Agricultural Experiment Station (KAES) and the National Institute of Food and Agriculture (NIFA), U.S. Department of Agriculture, Hatch–Multistate project #: 1007893. We also thank Dr. Janet Lumpp of the College of Engineering at the University of Kentucky for her help in reviewing this manuscript.

AUTHOR CONTRIBUTIONS

Akinbode Adedeji conceptualized the idea of the review paper, wrote some aspects, and reviewed the entire paper. Alfadhl Khaled structured and wrote most of the original draft. Chadwick Parrish assisted with the draft writing, structuring, and paper editing. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

ORCID

Alfadhl Y. Khaled https://orcid.org/0000-0001-5038-5971
Akinbode Adedeji https://orcid.org/0000-0002-3497-0166

REFERENCES

Abu-Ghoush, M., Fasfous, I., Al-Degs, Y., Al-Holy, M., Issa, A. A., Al-Reyahi, A. Y., & Alshathri, A. A. (2017). Application of mid-infrared spectroscopy and PLS-Kernel calibration for quick detection of pork in higher value meat mixes. *Journal of Food Measurement and Characterization*, *11*(1), 337–346. https://doi.org/10.1007/s11694-016-9402-4

Aït-Kaddour, A., Thomas, A., Mardon, J., Jacquot, S., Ferlay, A., & Gruffat, D. (2016). Potential of fluorescence spectroscopy to predict fatty acid composition of beef. *Meat Science*, *113*, 124–131. https://doi.org/10.1016/j.meatsci.2015.11.020

Alaiz-Rodriguez, R., & Parnell, A. C. (2020). A machine learning approach for lamb meat quality assessment using FTIR spectra. *IEEE Access*, *8*, 52385–52394. https://doi.org/10.1109/ACCESS.2020.2974623

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

Alshejari, A., & Kodogiannis, V. S. (2017). An intelligent decision support system for the detection of meat spoilage using multispectral images. *Neural Computing and Applications*, *28*(12), 3903–3920.

Amodio, M. L., Chaudhry, M. M. A., & Colelli, G. (2020). Spectral and hyperspectral technologies as an additional tool to increase information on quality and origin of horticultural crops. *Agronomy*, *10*(1), 1–10. https://doi.org/10.3390/agronomy10010007

Andersen, P. V., Wold, J. P., Gjerlaug-Enger, E., & Veiseth-Kent, E. (2018). Predicting post-mortem meat quality in porcine longissimus lumborum using Raman, near infrared and fluorescence spectroscopy. *Meat Science*, *145*(June), 94–100. https://doi.org/10.1016/j.meatsci.2018.06.016

Balage, J. M., da Luz e Silva, S., Gomide, C. A., de Nadai Bonin, M., & Figueira, A. C. (2015). Predicting pork quality using Vis/NIR spectroscopy. *Meat Science*, *108*, 37–43. https://doi.org/10.1016/j.meatsci.2015.04.018

Barbin, D., Elmasry, G., Sun, D. W., & Allen, P. (2012). Near-infrared hyperspectral imaging for grading and classification of pork. *Meat Science*, *90*(1), 259–268. https://doi.org/10.1016/j.meatsci.2011.07.011

Barbin, D. F., Elmasry, G., Sun, D. W., & Allen, P. (2013). Non-destructive determination of chemical composition in intact and minced pork using near-infrared hyperspectral imaging. *Food Chemistry*, *138*(2–3), 1162–1171. https://doi.org/10.1016/j.foodchem.2012.11.120

Barbin, D. F., Elmasry, G., Sun, D. W., Allen, P., & Morsy, N. (2013). Non-destructive assessment of microbial contamination in porcine meat using NIR hyperspectral imaging. *Innovative Food Science and Emerging Technologies*, *17*, 180–191. https://doi.org/10.1016/j.ifset.2012.11.001

Barbin, D. F., Mastelini, S. M., Barbon, S., Campos, G. F. C., Barbon, A. P. A. C., & Shimokomaki, M. (2016). Digital image analyses as an alternative tool for chicken quality assessment. *Biosystems Engineering*, *144*, 85–93. https://doi.org/10.1016/j.biosystemseng.2016.01.015

Barbon, S., C. Barbon, A. P. A. Da, Mantovani, R. G., & Barbin, D. F. (2018). Machine learning applied to near-infrared spectra for chicken meat classification. *Journal of Spectroscopy*, *2018*, 8949741. https://doi.org/10.1155/2018/8949741

Barbri, N., Halimi, A. & Rhofir, K. (2014). A nondestructive method based on an artificial vision for beef meat quality assesement. *International Journal of Innovative Research In Electrical, Electronics, Instrumentation and Control Engeineering*, *2*, 2060–2063.

Bhargava, A., & Bansal, A. (2020). Quality evaluation of Mono & bi-Colored Apples with computer vision and multispectral imaging. *Multimedia Tools and Applications*, *79*, 7857–7874.

Bhat, Z. F., Morton, J. D., Mason, S. L., & Bekhit, A. E. D. A. (2019). Does pulsed electric field have a potential to improve the quality of beef from older animals and how? *Innovative Food Science and Emerging Technologies*, *56*(April), 102194. https://doi.org/10.1016/j.ifset.2019.102194

Boyaci, I. H., Temiz, H. T., Uysal, R. S., Velioğlu, H. M., Yadegari, R. J., & Rishkan, M. M. (2014). A novel method for discrimination of beef and horsemeat using Raman spectroscopy. *Food Chemistry*, *148*, 37–41. https://doi.org/10.1016/j.foodchem.2013.10.006

Cafferky, J., Sweeney, T., Allen, P., Sahar, A., Downey, G., Cromie, A. R., & Hamill, R. M. (2020). Investigating the use of visible and near infrared spectroscopy to predict sensory and texture attributes of beef *M. longissimus thoracis et lumborum*. *Meat Science*, *159*(October 2018), 107915. https://doi.org/10.1016/j.meatsci.2019.107915

Chao, K., Yang, C. C., Chen, Y. R., Kim, M. S., & Chan, D. E. (2007). Hyperspectral-multispectral line-scan imaging system for automated poultry carcass inspection applications for food safety. *Poultry Science*, *86*(11), 2450–2460. https://doi.org/10.3382/ps.2006-00467

Chao, K., Yang, C.-C., & Kim, M. S. (2010). Spectral line-scan imaging system for high-speed non-destructive wholesomeness inspection of broilers. *Trends in Food Science & Technology*, *21*(3), 129–137.

Cheng, J. H., Nicolai, B., & Sun, D. W. (2017). Hyperspectral imaging with multivariate analysis for technological parameters prediction and classification of muscle foods: A review. *Meat Science*, *123*, 182–191. https://doi.org/10.1016/j.meatsci.2016.09.017

Chmiel, M., Słowiński, M., Dasiewicz, K., & Florowski, T. (2016). Use of computer vision system (CVS) for detection of PSE pork meat obtained from *M. semimembranosus*. *LWT - Food Science and Technology*, *65*, 532–536. https://doi.org/10.1016/j.lwt.2015.08.021

Choi, H. L., Hwang, B. K., Kim, B. S., & Choi, S. H. (2020). Influence of pathogen contamination on beef microbiota under different storage temperatures. *Food Research International*, *132*(February), 109118. https://doi.org/10.1016/j.foodres.2020.109118

Cubero, S., Aleixos, N., Moltó, E., Gómez-Sanchis, J., & Blasco, J. (2011). Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables. *Food and Bioprocess Technology*, *4*(4), 487–504. https://doi.org/10.1007/s11947-010-0411-8

Dasenaki, M. E., & Thomaidis, N. S. (2017). Meat safety: II Residues and contaminants. In F. Toldra (Ed.), *Lawrie's meat science* (pp. 553–583). Elsevier.

de Nadai Bonin, M., da Luz e Silva, S., Bünger, L., Ross, D., Dias Feijó, G. L., da Costa Gomes, R., Rennó, F. P., de Almeida Santana, M. H., de Rezende, F. M., Ítavo, L. C. V., de Novais, F. J., Surita, L. M. A., de Nadai Bonin, M., Pereira, M. W. F., & Ferraz, J. B. S. (2020). Predicting the shear value and intramuscular fat in meat from Nellore cattle using Vis-NIR spectroscopy. *Meat Science*, *163*(August 2019), 108077. https://doi.org/10.1016/j.meatsci.2020.108077

Del Olmo, A., Calzada, J., & Nuñez, M. (2014). Effect of high pressure processing and modified atmosphere packaging on the safety and quality of sliced ready-to-eat "lacón", a cured-cooked pork meat product. *Innovative Food Science and Emerging Technologies*, *23*, 25–32. https://doi.org/10.1016/j.ifset.2014.03.003

Du, D., Wang, J., Wang, B., Zhu, L., & Hong, X. (2019). Ripeness prediction of postharvest kiwifruit using a MOS e-nose combined with chemometrics. *Sensors*, *19*, 1–14. https://doi.org/10.3390/s19020419

Edita, R., Darius, G., Vinauskienė, R., Eisinaitė, V., Balčiūnas, G., Dobilienė, J., & Tamkutė, L. (2018). Rapid evaluation of fresh chicken meat quality by electronic nose. *Czech Journal of Food Sciences*, *36*(No. 5), 420–426. https://doi.org/10.17221/419/2017-cjfs

Estelles-Lopez, L., Ropodi, A., Pavlidis, D., Fotopoulou, J., Gkousari, C., Peyrodie, A., Panagou, E., Nychas, G.-J., & Mohareb, F. (2017). An automated ranking platform for machine learning regression models for meat spoilage prediction using multi-spectral imaging and metabolic profiling. *Food Research International*, *99*, 206–215.

Fan, K., Zhang, M., & Chen, H. (2020). Effect of ultrasound treatment combined with carbon dots coating on the microbial and physicochemical quality of fresh-cut cucumber. *Food and Bioprocess Technology*, *13*(4), 648–660. https://doi.org/10.1007/s11947-020-02424-x

Fang, Y., & Ramasamy, R. P. (2015). Current and prospective methods for plant disease detection. *Biosensors*, *5*(3), 537–561. https://doi.org/10.3390/bios5030537

Feng, C.-H., Makino, Y., Oshita, S., & Martin, J. F. G. (2018). Hyperspectral imaging and multispectral imaging as the novel techniques for detecting defects in raw and processed meat products: Current state-of-the-art research advances. *Food Control*, *84*, 165–176.

Feng, Y. Z., & Sun, D. W. (2013). Determination of total viable count (TVC) in chicken breast fillets by near-infrared hyperspectral imaging and spectroscopic transforms. *Talanta*, *105*, 244–249. https://doi.org/10.1016/j.talanta.2012.11.042

Fowler, S. M., Morris, S., & Hopkins, D. L. (2020). Preliminary investigation for the prediction of intramuscular fat content of lamb in-situ using a hand-held NIR spectroscopic device. *Meat Science*, *166*(December 2019), 108153. https://doi.org/10.1016/j.meatsci.2020.108153

Furutani, S., Hagihara, Y., & Nagai, H. (2017). On-site identification of meat species in processed foods by a rapid real-time polymerase chain reaction system. *Meat Science*, *131*, 56–59.

Geronimo, B. C., Mastelini, S. M., Carvalho, R. H., Barbon Júnior, S., Barbin, D. F., Shimokomaki, M., & Ida, E. I. (2019). Computer vision system and near-infrared spectroscopy for identification and classification of chicken with wooden breast, and physicochemical and technological characterization. *Infrared Physics and Technology*, *96*, 303–310. https://doi.org/10.1016/j.infrared.2018.11.036

Girolami, A., Napolitano, F., Faraone, D., & Braghieri, A. (2013). Measurement of meat color using a computer vision system. *Meat Science*, *93*(1), 111–118. https://doi.org/10.1016/j.meatsci.2012.08.010

Gliszczyńska-Świgło, A., & Chmielewski, J. (2017). Electronic nose as a tool for monitoring the authenticity of food. A review. *Food Analytical Methods*, *10*(6), 1800–1816. https://doi.org/10.1007/s12161-016-0739-4

Grassi, S., Casiraghi, E., & Alamprese, C. (2018). Handheld NIR device: A non-targeted approach to assess authenticity of fish fillets and patties. *Food Chemistry*, *243*(May 2017), 382–388. https://doi.org/10.1016/j.foodchem.2017.09.145

Hart, C. E., Hayes, D. J., Jacobs, K. L., Schulz, L. L., & Crespi, J. M. (2020). *The impact of COVID-19 on Iowa's corn, soybean, ethanol, pork, and beef sectors chad*. Center for Agricultural and Rural Development, Iowa State University. https://www.card.iastate.edu/products/publications/pdf/20pb28.pdf

Hong, X. Z., Wei, Z. B., Hai, Z., & Wang, J. (2014). Application of electronic nose and neural network in beef freshness detection. *Modern Food Science and Technology*, *30*, 278–284.

Huang, L., Zhao, J., Chen, Q., & Zhang, Y. (2013). Rapid detection of total viable count (TVC) in pork meat by hyperspectral imaging. *Food Research International*, *54*(1), 821–828. https://doi.org/10.1016/j.foodres.2013.08.011

Huang, Q., Chen, Q., Li, H., Huang, G., Ouyang, Q., & Zhao, J. (2015). Non-destructively sensing pork's freshness indicator using near infrared multispectral imaging technique. *Journal of Food Engineering*, *154*, 69–75. https://doi.org/10.1016/j.jfoodeng.2015.01.006

Iqbal, A., Sun, D. W., & Allen, P. (2013). Prediction of moisture, color and pH in cooked, pre-sliced turkey hams by NIR hyperspectral imaging system. *Journal of Food Engineering*, *117*(1), 42–51. https://doi.org/10.1016/j.jfoodeng.2013.02.001

Jia, W., Liang, G., Wang, Y., & Wang, J. (2018). Electronic noses as a powerful tool for assessing meat quality: A mini review. *Food Analytical Methods*, *11*(10), 2916–2924. https://doi.org/10.1007/s12161-018-1283-1

Jiang, H., Yoon, S. C., Zhuang, H., Wang, W., Lawrence, K. C., & Yang, Y. (2018). Tenderness classification of fresh broiler breast fillets using visible and near-infrared hyperspectral imaging. *Meat Science*, *139*(January), 82–90. https://doi.org/10.1016/j.meatsci.2018.01.013

Johnson, R. (2014). *Food fraud and "Economically motivated adulteration" of food and food ingredients*. Congressional Research Service.

Kademi, H. I., Ulusoy, B. H., & Hecer, C. (2019). Applications of miniaturized and portable near infrared spectroscopy (NIRS) for inspection and control of meat and meat products. *Food Reviews International*, *35*(3), 201–220. https://doi.org/10.1080/87559129.2018.1514624

Kamruzzaman, M., Elmasry, G., Sun, D. W., & Allen, P. (2012). Non-destructive prediction and visualization of chemical composition in lamb meat using NIR hyperspectral imaging and multivariate regression. *Innovative Food Science and Emerging Technologies*, *16*, 218–226. https://doi.org/10.1016/j.ifset.2012.06.003

Kamruzzaman, M., Makino, Y., & Oshita, S. (2015). Non-invasive analytical technology for the detection of contamination, adulteration, and authenticity of meat, poultry, and fish: A review. *Analytica Chimica Acta*, *853*(1), 19–29. https://doi.org/10.1016/j.aca.2014.08.043

Kamruzzaman, M., Makino, Y., & Oshita, S. (2016). Rapid and non-destructive detection of chicken adulteration in minced beef using visible near-infrared hyperspectral imaging and machine learning. *Journal of Food Engineering*, *170*, 8–15. https://doi.org/10.1016/j.jfoodeng.2015.08.023

Kamruzzaman, M., Sun, D. W., ElMasry, G., & Allen, P. (2013). Fast detection and visualization of minced lamb meat adulteration using NIR hyperspectral imaging and multivariate image analysis. *Talanta*, *103*, 130–136. https://doi.org/10.1016/j.talanta.2012.10.020

Khaled, A. Y., Aziz, S. A., Bejo, S. K., Nawia, N. M., Semanc, I. A., & Onwude, D. I. (2018). Early detection of diseases in plant tissue using spectroscopy – Applications and limitations. *Applied Spectroscopy Reviews*, *53*(1), 36–64.

Khoshnoudi-Nia, S., Moosavi-Nasab, M., Nassiri, S. M., & Azimifar, Z. (2018). Determination of total viable count in rainbow-trout fish fillets based on hyperspectral imaging system and different variable selection and extraction of reference data methods. *Food Analytical Methods*, *11*(12), 3481–3494.

Khulal, U., Zhao, J., Hu, W., & Chen, Q. (2016). Nondestructive quantifying total volatile basic nitrogen (TVB-N) content in chicken using hyperspectral imaging (HSI) technique combined with different data dimension reduction algorithms. *Food Chemistry*, *197*, 1191–1199. https://doi.org/10.1016/j.foodchem.2015.11.084

Khulal, U., Zhao, J., Hu, W., & Chen, Q. (2017). Intelligent evaluation of total volatile basic nitrogen (TVB-N) content in chicken meat by an improved multiple level data fusion model. *Sensors and Actuators, B: Chemical*, *238*, 337–345. https://doi.org/10.1016/j.snb.2016.07.074

Kiani, S., Minaei, S., & Ghasemi-Varnamkhasti, M. (2016). A portable electronic nose as an expert system for aroma-based classification of saffron. *Chemometrics and Intelligent Laboratory Systems*, *156*, 148–156. https://doi.org/10.1016/j.chemolab.2016.05.013

Kim, H., Kim, D., Kim, H., Song, S., & Song, Y. (2018). Evaluation of the microbiological status of raw beef in Korea : Considering the suitability of aerobic plate count guidelines. *Korean Journal for Food Science of Animal Resources Korean*, *38*(1), 43–51.

Kim, I., Xu, C., & Kim, M. S. (2006). Poultry skin tumor detection in hyperspectral images using radial basis probabilistic neural network. In J. Wang, Z. Yi, J. M. Zurada, B. L. Lu, & H. Yin (Eds.), *International Symposium on Neural Networks: Advances in neural networks - ISNN 2006* (pp. 770–776). Springer.

Konda Naganathan, G., Cluff, K., Samal, A., Calkins, C. R., Jones, D. D., Meyer, G. E., & Subbiah, J. (2016). Three dimensional chemometric analyses of hyperspectral images for beef tenderness forecasting. *Journal of Food Engineering*, *169*, 309–320. https://doi.org/10.1016/j.jfoodeng.2015.09.001

Lambe, N. R., McLean, K. A., Gordon, J., Evans, D., Clelland, N., & Bunger, L. (2017). Prediction of intramuscular fat content using CT scanning of packaged lamb cuts and relationships with meat eating quality. *Meat Science*, *123*, 112–119. https://doi.org/10.1016/j.meatsci.2016.09.008

Lan, W., Jaillais, B., Leca, A., Renard, C. M. G. C., & Bureau, S. (2020). A new application of NIR spectroscopy to describe and predict purees quality from the non-destructive apple measurements. *Food Chemistry*, *310*(May 2019), 125944. https://doi.org/10.1016/j.foodchem.2019.125944

Li, H., Chen, Q., Zhao, J., & Ouyang, Q. (2014). Non-destructive evaluation of pork freshness using a portable electronic nose (E-nose) based on a colorimetric sensor array. *Analytical Methods*, *6*(16), 6271–6277. https://doi.org/10.1039/c4ay00014e

Li, H., Sun, X., Pan, W., Kutsanedzie, F., Zhao, J., & Chen, Q. (2016). Feasibility study on nondestructively sensing meat's freshness using light scattering imaging technique. *Meat Science*, *119*, 102–109. https://doi.org/10.1016/j.meatsci.2016.04.031

Li, Z., Askim, J. R., & Suslick, K. S. (2018). The optoelectronic nose: Colorimetric and fluorometric sensor arrays. *Chemical Reviews*, *119*(1), 231–292.

Lim, J., Lee, A., Kang, J., Seo, Y., Kim, B., Kim, G., & Kim, S. (2020). Non-destructive detection of bone fragments embedded in meat using hyperspectral reflectance imaging technique. *Sensors*, *20*(14), 4038.

Limbo, S., Sinelli, N., Torri, L., & Riva, M. (2009). Freshness decay and shelf life predictive modelling of European sea bass (*Dicentrarchus labrax*) applying chemical methods and electronic nose. *LWT - Food Science and Technology*, *42*(5), 977–984. https://doi.org/10.1016/j.lwt.2008.12.011

Liu, H., Ji, Z., Liu, X., Shi, C., & Yang, X. (2020). Non-destructive determination of chemical and microbial spoilage indicators of beef for freshness evaluation using front-face synchronous fluorescence spectroscopy. *Food Chemistry*, *321*, 126628. https://doi.org/10.1016/j.foodchem.2020.126628

Liu, J., Cao, Y., Wang, Q., Pan, W., Ma, F., Liu, C., Chen, W., Yang, J., & Zheng, L. (2016). Rapid and non-destructive identification of water-injected beef samples using multispectral imaging analysis. *Food Chemistry*, *190*, 938–943. https://doi.org/10.1016/j.foodchem.2015.06.056

Liu, J. H., Sun, X., Young, J. M., Bachmeier, L. A., & Newman, D. J. (2018). Predicting pork loin intramuscular fat using computer vision system. *Meat Science*, *143*(March), 18–23. https://doi.org/10.1016/j.meatsci.2018.03.020

López-Maestresalas, A., Insausti, K., Jarén, C., Pérez-Roncal, C., Urrutia, O., Beriain, M. J., & Arazuri, S. (2019). Detection of minced lamb and beef fraud using NIR spectroscopy. *Food Control*, *98*, 465–473. https://doi.org/10.1016/j.foodcont.2018.12.003

Lu, W., Wu, Y., Guo, Q., Ren, L., Zhu, P., Xu, L., Chang, G., & Chen, G. (2017). Establishment of a freshness-evaluating standard for chilled yellow chicken meat. *Food Analytical Methods*, *10*(8), 2629–2635. https://doi.org/10.1007/s12161-017-0815-4

Ma, F., Qin, H., Zhou, C., Wang, X., Chen, C., & Zheng, L. (2016). Rapid and non-destructive detection of iron porphyrin content in pork using multispectral imaging approach. *Food Analytical Methods*, *9*(5), 1180–1187.

Mancini, M., Mazzoni, L., Gagliardi, F., Balducci, F., Duca, D., Toscano, G., Mezzetti, B., & Capocasa, F. (2020). Application of the non-destructive NIR technique for the evaluation of strawberry fruits quality parameters. *Foods*, *9*(4), 441. https://doi.org/10.3390/foods9040441

Mewa, E. A., Okoth, M. W., Kunyanga, C. N., & Rugiri, M. N. (2018). Effect of drying air temperature and slice thickness on the physical and microbiological quality of dried beef. *LWT - Food Science and Technology*, *92*, 484–489. https://doi.org/10.1016/j.lwt.2018.02.068

Naganathan, G. K., Cluff, K., Samal, A., Calkins, C. R., Jones, D. D., Meyer, G. E., & Subbiah, J. (2016). Three dimensional chemometric analyses of hyperspectral images for beef tenderness forecasting. *Journal of Food Engineering*, *169*, 309–320.

Nakariyakul, S., & Casasent, D. P. (2009). Fast feature selection algorithm for poultry skin tumor detection in hyperspectral data. *Journal of Food Engineering*, *94*(3–4), 358–365. https://doi.org/10.1016/j.jfoodeng.2009.04.001

Nurjuliana, M., Che Man, Y. B., Mat Hashim, D., & Mohamed, A. K. S. (2011). Rapid identification of pork for halal authentication using the electronic nose and gas chromatography mass spectrometer with headspace analyzer. *Meat Science*, *88*(4), 638–644. https://doi.org/10.1016/j.meatsci.2011.02.022

Oliveri, P., López, M. I., Casolino, M. C., Ruisánchez, I., Callao, M. P., Medini, L., & Lanteri, S. (2014). Partial least squares density modeling (PLS-DM) - A new class-modeling strategy applied to the authentication of olives in brine by near-infrared spectroscopy. *Analytica Chimica Acta*, *851*(C), 30–36. https://doi.org/10.1016/j.aca.2014.09.013

Panagou, E. Z., Papadopoulou, O., Carstensen, J. M., & Nychas, G. J. E. (2014). Potential of multispectral imaging technology for rapid and non-destructive determination of the microbiological quality of beef filets during aerobic storage. *International Journal of Food Microbiology*, *174*, 1–11. https://doi.org/10.1016/j.ijfoodmicro.2013.12.026

Parlapani, F. F., Haroutounian, S. A., Nychas, G. J. E., & Boziaris, I. S. (2015). Microbiological spoilage and volatiles production of gutted European sea bass stored under air and commercial modified atmosphere package at 2°C. *Food Microbiology*, *50*, 44–53. https://doi.org/10.1016/j.fm.2015.03.006

Peña-González, E. M., Alarcón-Rojo, A. D., Rentería, A., García, I., Santellano, E., Quintero, A., & Luna, L. (2017). Quality and sensory profile of ultrasound-treated beef. *Italian Journal of Food Science*, *29*(3), 463–476.

Peng, Y., & Dhakal, S. (2015). Optical methods and techniques for meat quality inspection. *Transactions of the ASABE*, *58*(5), 1371–1386. https://doi.org/10.13031/trans.58.11004

Pophiwa, P., Webb, E. C., & Frylinck, L. (2020). A review of factors affecting goat meat quality and mitigating strategies. *Small Ruminant Research*, *183*(August 2019), 106035. https://doi.org/10.1016/j.smallrumres.2019.106035

Premanandh, J. (2013). Horse meat scandal - A wake-up call for regulatory authorities. *Food Control*, *34*(2), 568–569. https://doi.org/10.1016/j.foodcont.2013.05.033

Prieto, N., López-Campos, Ó., Aalhus, J. L., Dugan, M. E. R., Juárez, M., & Uttaro, B. (2014). Use of near infrared spectroscopy for estimating meat chemical composition, quality traits and fatty acid content from cattle fed sunflower or flaxseed. *Meat Science*, *98*(2), 279–288. https://doi.org/10.1016/j.meatsci.2014.06.005

Prieto, N., Roehe, R., Lavín, P., Batten, G., & Andrés, S. (2009). Application of near infrared reflectance spectroscopy to predict meat and meat products quality: A review. *Meat Science*, *83*(2), 175–186. https://doi.org/10.1016/j.meatsci.2009.04.016

Prieto, N., Pawluczyk, O., Dugan, M. E. R., & Aalhus, J. L. (2017). A review of the principles and applications of near-infrared spectroscopy to characterize meat, fat, and meat products. *Applied Spectroscopy*, *71*(7), 1403–1426. https://doi.org/10.1177/0003702817709299

Przybylak, A., Ślósarz, P., Boniecki, P., Koszela, K., Przybył, K., Wojcieszak, D., Szulc, R., Ludwiczak, A., & Górna, K. (2015). Marbling classification of lambs carcasses with the artificial neural image analysis. *Seventh International Conference on Digital Image Processing (ICDIP 2015)*, *9631*, 963113. https://doi.org/10.1117/12.2197027

Pu, H., Kamruzzaman, M., & Sun, D. W. (2015). Selection of feature wavelengths for developing multispectral imaging systems for quality, safety and authenticity of muscle foods-a review. *Trends in Food Science and Technology*, *45*(1), 86–104. https://doi.org/10.1016/j.tifs.2015.05.006

Rady, A., & Adedeji, A. (2018). Assessing different processed meats for adulterants using visible-near-infrared spectroscopy. *Meat Science*, *136*, 59–67. https://doi.org/10.1016/j.meatsci.2017.10.014

Rady, A., & Adedeji, A. A. (2020). Application of hyperspectral imaging and machine learning methods to detect and quantify adulterants in minced meats. *Food Analytical Methods*, *13*(4), 970–981. https://doi.org/10.1007/s12161-020-01719-1

Ramírez, H. L., Soriano, A., Gómez, S., Iranzo, J. U., & Briones, A. I. (2018). Evaluation of the Food Sniffer electronic nose for assessing the shelf life of fresh pork meat compared to physicochemical measurements of meat quality. *European Food Research and Technology*, *244*(6), 1047–1055. https://doi.org/10.1007/s00217-017-3021-0

Ripoll, G., Lobón, S., & Joy, M. (2018). Use of visible and near infrared reflectance spectra to predict lipid peroxidation of light lamb meat and discriminate dam's feeding systems. *Meat Science*, *143*(April), 24–29. https://doi.org/10.1016/j.meatsci.2018.04.006

Ropodi, A. I., Panagou, E. Z., & Nychas, G.-J. E. (2017). Multispectral imaging (MSI): A promising method for the detection of minced beef adulteration with horsemeat. *Food Control*, *73*, 57–63.

Ropodi, A. I., Panagou, E. Z., & Nychas, G.-J. E. (2018). Rapid detection of frozen-then-thawed minced beef using multispectral imaging and Fourier transform infrared spectroscopy. *Meat Science*, *135*, 142–147.

Ropodi, A. I., Pavlidis, D. E., Mohareb, F., Panagou, E. Z., & Nychas, G.-J. (2015). Multispectral image analysis approach to detect adulteration of beef and pork in raw meats. *Food Research International*, *67*, 12–18.

Ruedt, C., Gibis, M., & Weiss, J. (2020). Quantification of surface iridescence in meat products by digital image analysis. *Meat Science*, *163*(July 2019), 108064. https://doi.org/10.1016/j.meatsci.2020.108064

Säde, E., Murros, A., & Björkroth, J. (2013). Predominant enterobacteria on modified-atmosphere packaged meat and poultry. *Food Microbiology*, *34*(2), 252–258. https://doi.org/10.1016/j.fm.2012.10.007

Sahar, A., Allen, P., Sweeney, T., Cafferky, J., Downey, G., Cromie, A., & Hamill, R. M. (2019). Online prediction of physico-chemical quality attributes of beef using visible–near-infrared spectroscopy and chemometrics. *Foods*, *8*(11), 1–12. https://doi.org/10.3390/foods8110525

Sanaeifar, A., ZakiDizaji, H., Jafari, A., & Guardia, M. d. l. (2017). Early detection of contamination and defect in foodstuffs by electronic nose: A review. *TrAC - Trends in Analytical Chemistry*, *97*, 257–271. https://doi.org/10.1016/j.trac.2017.09.014

Sanz, J. A., Fernandes, A. M., Barrenechea, E., Silva, S., Santos, V., Gonçalves, N., Paternain, D., Jurio, A., & Melo-Pinto, P. (2016). Lamb muscle discrimination using hyperspectral imaging: Comparison of various machine learning algorithms. *Journal of Food Engineering*, *174*, 92–100. https://doi.org/10.1016/j.jfoodeng.2015.11.024

Saricaoglu, F. T., & Turhan, S. (2019). Performance of mechanically deboned chicken meat protein coatings containing thyme or clove essential oil for storage quality improvement of beef sucuks. *Meat Science*, *158*, 107912.

Saucier, L. (2016). Microbial spoilage, quality and safety within the context of meat sustainability. *Meat Science*, *120*, 78–84. https://doi.org/10.1016/j.meatsci.2016.04.027

Savoia, S., Albera, A., Brugiapaglia, A., Di Stasio, L., Ferragina, A., Cecchinato, A., & Bittante, G. (2020). Prediction of meat quality traits in the abattoir using portable and hand-held near-infrared spectrometers. *Meat Science*, *161*(July 2019), 108017. https://doi.org/10.1016/j.meatsci.2019.108017

Sendin, K., Manley, M., & Williams, P. J. (2018). Classification of white maize defects with multispectral imaging. *Food Chemistry*, *243*, 311–318.

Shenoy, J. (2016). *IOT in agriculture*. 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom).

Shi, C., Qian, J., Zhu, W., Liu, H., Han, S., & Yang, X. (2019). Nondestructive determination of freshness indicators for tilapia fillets stored at various temperatures by hyperspectral imaging coupled with RBF neural networks. *Food Chemistry*, *275*(April 2018), 497–503. https://doi.org/10.1016/j.foodchem.2018.09.092

Shi, S., Kong, B., Wang, Y., Liu, Q., & Xia, X. (2020). Comparison of the quality of beef jerky processed by traditional and modern drying methods from different districts in Inner Mongolia. *Meat Science*, *163*(108080).

Siripatrawan, U. (2018). Hyperspectral imaging for rapid evaluation and visualization of quality deterioration index of vacuum packaged dry-cured sausages. *Sensors and Actuators, B: Chemical*, *254*, 1025–1032. https://doi.org/10.1016/j.snb.2017.07.006

Song, X., Gao, S. T., Hang, M. X., Chen, W., Chen, L., Liu, Y., & Zhang, J. J. (2015). Application of electronic nose on origin identification and quality grade evaluation of Jinhua and Xuanwei ham. *Food and Machinery*, *31*, 114–118.

Song, Y., Luo, Y., You, J., & Hu, S. (2012). Biochemical, sensory and microbiological attributes of bream (*Megalobrama amblycephala*) during partial freezing and chilled storage. *Journal of the Science of Food and Agriculture*, *92*(1), 197–202. https://doi.org/10.1002/jsfa.4572

Spink, J., & Moyer, D. C. (2011). Defining the public health threat of food fraud. *Journal of Food Science*, *76*(9), R157–R163. https://doi.org/10.1111/j.1750-3841.2011.02417.x

Spyrelli, E. D., Ozcan, O., Mohareb, F., Panagou, E. Z., & Nychas, G.-J. E. (2021). Spoilage assessment of chicken breast fillets by means of Fourier transform infrared spectroscopy and multispectral image analysis. *Current Research in Food Science*, *4*, 121–131.

Su, W.-H., & Sun, D.-W. (2018). Multispectral imaging for plant food quality analysis and visualization. *Comprehensive Reviews in Food Science and Food Safety*, *17*(1), 220–239.

Sujiwo, J., Kim, H. J., Song, S. O., & Jang, A. (2019). Relationship between quality and freshness traits and torrymeter value of beef loin during cold storage. *Meat Science*, *149*(June 2018), 120–125. https://doi.org/10.1016/j.meatsci.2018.11.017

Sun, T. L., Yue, X. Q., Zhang, P., Li, J. K., & Zhang, P. (2014). The electronic nose usage in predicting the freshness of beef at freezing point storage. *Food Ferm Ind*, *4*, 185–189.

Sun, X., Young, J., Liu, J. H., & Newman, D. (2018). Prediction of pork loin quality using online computer vision system and artificial intelligence model. *Meat Science*, *140*(November 2017), 72–77. https://doi.org/10.1016/j.meatsci.2018.03.005

Taheri-Garavand, A., Fatahi, S., Omid, M., & Makino, Y. (2019). Meat quality evaluation based on computer vision technique: A review. *Meat Science*, *156*(May), 183–195. https://doi.org/10.1016/j.meatsci.2019.06.002

Taheri-Garavand, A., Fatahi, S., Shahbazi, F., & de la Guardia, M. (2019). A nondestructive intelligent approach to real-time evaluation of chicken meat freshness based on computer vision technique. *Journal of Food Process Engineering*, *42*(4), 1–10. https://doi.org/10.1111/jfpe.13039

Tao, F., Peng, Y., Li, Y., Chao, K., & Dhakal, S. (2012). Simultaneous determination of tenderness and Escherichia coli contamination of pork using hyperspectral scattering technique. *Meat Science*, *90*(3), 851–857.

Tao, F., & Peng, Y. (2014). A nondestructive method for prediction of total viable count in pork meat by hyperspectral scattering imaging. *Food and Bioprocess Technology*, *8*(1), 17–30. https://doi.org/10.1007/s11947-014-1374-y

Teimouri, N., Omid, M., Mollazade, K., Mousazadeh, H., Alimardani, R., & Karstoft, H. (2018). On-line separation and sorting of chicken portions using a robust vision-based intelligent modelling approach. *Biosystems Engineering*, *167*, 8–20. https://doi.org/10.1016/j.biosystemseng.2017.12.009

Timsorn, K., Thoopboochagorn, T., Lertwattanasakul, N., & Wongchoosuk, C. (2016). Evaluation of bacterial population on chicken meats using a briefcase electronic nose. *Biosystems Engineering*, *151*, 116–125. https://doi.org/10.1016/j.biosystemseng.2016.09.005

Tomasevic, I., Tomovic, V., Milovanovic, B., Lorenzo, J., Đorđević, V., Karabasil, N., & Djekic, I. (2019). Comparison of a computer vision system vs. traditional colorimeter for color evaluation of meat products with various physical properties. *Meat Science*, *148*(April 2018), 5–12. https://doi.org/10.1016/j.meatsci.2018.09.015

United States Department of Agriculture (USDA). (1997). *United States standards for grades of carcass beef*. Author.

Velásquez, L., Cruz-Tirado, J. P., Siche, R., & Quevedo, R. (2017). An application based on the decision tree to classify the marbling of beef by hyperspectral imaging. *Meat Science*, *133*(May), 43–50. https://doi.org/10.1016/j.meatsci.2017.06.002

Verplanken, K., Wauters, J., Vercruysse, V., Aluwé, M., & Vanhaecke, L. (2017). Sensory evaluation of boar-taint-containing minced meat, dry-cured ham and dry fermented sausage by a trained expert panel and consumers. *Food Chemistry*, *233*, 247–255. https://doi.org/10.1016/j.foodchem.2017.04.105

Wang, W., Peng, Y., Huang, H., & Wu, J. (2011). Application of hyperspectral imaging technique for the detection of total viable bacteria count in pork. *Sensor Letters*, *9*(3), 1024–1030.

Wang, W., Peng, Y., Sun, H., Zheng, X., & Wei, W. (2018a). Realtime inspection of pork quality attributes using dual-band spectroscopy. *Journal of Food Engineering*, *237*(November 2017), 103–109. https://doi.org/10.1016/j.jfoodeng.2018.05.022

Wang, W., Peng, Y., Sun, H., Zheng, X., & Wei, W. (2018b). Spectral detection techniques for non-destructively monitoring the quality, safety, and classification of fresh red meat. *Food Analytical Methods*, *11*(10), 2707–2730. https://doi.org/10.1007/s12161-018-1256-4

Wang, W., Zhang, H., Yan, L., Zhou, H., Chen, C., Xu, B., Zheng, L., & Ma, F. (2021). A rapid and non-destructive approach to identify bone fragments embedded in lean pork slices based on multispectral imaging and chemometrics. *Infrared Physics & Technology*, *113*, 103575.

Weng, S., Yu, S., Dong, R., Pan, F., & Liang, D. (2020). Nondestructive detection of storage time of strawberries using visible/near-infrared hyperspectral imaging. *International Journal of Food Properties*, *23*(1), 269–281. https://doi.org/10.1080/10942912.2020.1716793

Wijaya, D. R., Sarno, R., Zulaika, E., & Sabila, S. I. (2017). Development of mobile electronic nose for beef quality monitoring.

Procedia Computer Science, *124*, 728–735. https://doi.org/10.1016/j.procs.2017.12.211

Wojnowski, W., Majchrzak, T., Dymerski, T., Gębicki, J., & Namieśnik, J. (2017). Poultry meat freshness evaluation using electronic nose technology and ultra-fast gas chromatography. *Monatshefte Fur Chemie*, *148*(9), 1631–1637. https://doi.org/10.1007/s00706-017-1969-x

Xiao-wei, H., Xiao-bo, Z., Ji-yong, S., Zhi-hua, L., & Jie-wen, Z. (2018). Colorimetric sensor arrays based on chemo-responsive dyes for food odor visualization. *Trends in Food Science & Technology*, *81*, 90–107.

Xinhua, J., Heru, X., Lina, Z., Xiaojing, G., Guodong, W., & Jie, B. (2018). Nondestructive detection of chilled mutton freshness based on multi-label information fusion and adaptive BP neural network. *Computers and Electronics in Agriculture*, *155*(October), 371–377. https://doi.org/10.1016/j.compag.2018.10.019

Xiong, Z., Xie, A., Sun, D. W., Zeng, X. A., & Liu, D. (2015). Applications of hyperspectral imaging in chicken meat safety and quality detection and evaluation: A review. *Critical Reviews in Food Science and Nutrition*, *55*(9), 1287–1301. https://doi.org/10.1080/10408398.2013.834875

Xu, M., Wang, J., & Zhu, L. (2019). The qualitative and quantitative assessment of tea quality based on E-nose, E-tongue and E-eye combined with chemometrics. *Food Chemistry*, *289*(March), 482–489. https://doi.org/10.1016/j.foodchem.2019.03.080

Yan, M., Lu, Y., & Chen, D. (2015). Application of electronic nose in freshness evaluation of tilapia fillets as affected by ozone treatment. *Food Science*, *2015*(20), 51.

Yao, X., Cai, F., Zhu, P., Fang, H., Li, J., & He, S. (2019). Non-invasive and rapid pH monitoring for meat quality assessment using a low-cost portable hyperspectral scanner. *Meat Science*, *152*(November 2018), 73–80. https://doi.org/10.1016/j.meatsci.2019.02.017

Yoon, S. C., Park, B., Lawrence, K. C., Windham, W. R., & Heitschmidt, G. W. (2011). Line-scan hyperspectral imaging system for real-time inspection of poultry carcasses with fecal material and ingesta. *Computers and Electronics in Agriculture*, *79*(2), 159–168. https://doi.org/10.1016/j.compag.2011.09.008

Zapotoczny, P., Szczypiński, P. M., & Daszkiewicz, T. (2016). Evaluation of the quality of cold meats by computer-assisted image analysis. *LWT - Food Science and Technology*, *67*, 37–49. https://doi.org/10.1016/j.lwt.2015.11.042

Zhang, B., Huang, W., Gong, L., Li, J., Zhao, C., Liu, C., & Huang, D. (2015). Computer vision detection of defective apples using automatic lightness correction and weighted RVM classifier. *Journal of Food Engineering*, *146*, 143–151. https://doi.org/10.1016/j.jfoodeng.2014.08.024

Zhang, W., Naveena, B. M., Jo, C., Sakata, R., Zhou, G., Banerjee, R., & Nishiumi, T. (2017). Technological demands of meat processing–An Asian perspective. *Meat Science*, *132*, 35–44.

Zvereva, E. A., Kovalev, L. I., Ivanov, A. V., Kovaleva, M. A., Zherdev, A. V., Shishkin, S. S., Lisitsyn, A. B., Chernukha, I. M., & Dzantiev, B. B. (2015). Enzyme immunoassay and proteomic characterization of troponin I as a marker of mammalian muscle compounds in raw meat and some meat products. *Meat Science*, *105*, 46–52. https://doi.org/10.1016/j.meatsci.2015.03.001

How to cite this article: Khaled, Alfadhl Y, Parrish, Chadwick A, & Adedeji, Akinbode. Emerging nondestructive approaches for meat quality and safety evaluation—A review. *Compr Rev Food Sci Food Saf*. 2021;*20:* 3438–3463. https://doi.org/10.1111/1541-4337.12781