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ABSTRACT

Meat is highly perishable and poses health threats when its quality and safety is unmonitored. Chemical methods of quality and safety determination are expensive, time-consuming and lack real-time monitoring applicability. Nondestructive techniques have been reported as antidotes to these constraints. This paper assessed the potential of nondestructive techniques such as near-infrared spectroscopy, hyperspectral imaging, multispectral imaging, e-nose, and their data fusion, all combined with algorithms for quality monitoring of pork, beef, and chicken, the most consumed meat sources in the world. These techniques combined with data processing applications may offer a panacea for real-time industrial meat quality and safety monitoring.

KEYWORDS

Nondestructive technique; multivariate algorithms; odor sensing; optical techniques; quality and safety

Introduction

There has always been the demand for the consumption of quality meat as a result of their associated benefits in the human diet.[1] Its ease of perishability and contamination reported in various studies has increased awareness among consumers and producers because of its imminent health threats and damages, respectively. These concerns of consumers and producers in the meat industry are borne out of the high rate of quality and safety incidents recorded. There has been a surge in the demand for high-quality meat and meat products by consumers from meat producers. Meat quality and safety definition is complex and has been reported to be evolving and expanding to capture meat properties from the point of production to consumption.[1] It has been defined to encompass the intrinsic and extrinsic attributes of meat that make it safe and acceptable by consumers.[1,2] The intrinsic attributes refer to the meat properties such its technological traits such as texture, water holding capacity (WHC), and color[2], consumer acceptability or sensory traits such as flavor, tenderness, juiciness[3], nutritional attributes such as fatty acid composition, protein, intramuscular fat, and lipids,[1] and safety attributes including microbial loads, physical, and chemical residues.[4–6] However, its extrinsic attributes are related to the meat production system such as breeding, animal welfare, and marketing variables like branding, labeling, and pricing.[2] This review on meat quality and safety is restricted to the use of nondestructive tools combined with multivariate algorithms to monitor the intrinsic attributes of chicken, pork, and beef.

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Over the years, conventional chemical procedures, instrumental methods, sensory analysis, and screening methods have been used for meat quality and safety prediction. These methods are destructive, subjective, cost-intensive, laborious, invasive and lack real-time meat monitoring applicability.[7] These demerits render them less-efficient in monitoring meat quality and safety with increase in meat production. Emerging techniques such as near-infrared (NIR) spectroscopy, computer vision, hyperspectral imaging (HSI), multispectral imaging (MSI), electronic nose (e-nose), nuclear magnetic resonance imaging (NMRI), ultrasonic analysis, X-ray imaging and computer tomography (CT); have been reported to be noninvasive, cost-effective, environmentally friendly, as well as capable of providing rapid and reproducible results for quality and safety monitoring of meat.[8] These afore-listed technologies are combined with various multivariate algorithms for the monitoring of quality and safety of meat samples. However, the past decades have seen the increased use of NIRS, HSI, MSI, and e-nose techniques combined with various multivariate algorithms for the monitoring of meat quality attributes. All of these emerging nondestructive techniques have unique weaknesses and strengths. Hence, there is a need to identify, select and review nondestructive technologies that are most efficient and have high potentials for real-time monitoring of meat quality and safety towards meat quality assurance becomes relevant. Moreover, the bulk of the world's meat is currently supplied by pork (36%), poultry (35%), beef (22%) and other animals (7%).[9] Therefore, the successful application of the selected nondestructive techniques for monitoring meat quality and safety of these meat sources on real-time basis is of relevance to the meat industry.

Although various nondestructive techniques for food quality and safety monitoring have been reported in studies, the potentials of selected nondestructive techniques such as NIRS, HSI, MSI, E-nose based on MOS (metal oxide sensors) and CSA (colorimetric sensor arrays) for real-time quality and safety monitoring of pork, beef and chicken, which are the largest sources of global meat production and consumption have not been reviewed. Moreover, the application of most of these selected techniques have been at the laboratory levels but growth in the meat industry has necessitated a shift towards real-time monitoring of meat quality and safety along the whole processing line, in order to guarantee high-quality meat products for consumers. This review, therefore, assessed the distinctive and collective characteristics of NIRS, HSI, MSI, E-nose based on MOS and CSA to explore their potential for real-time quality and safety monitoring at the industrial level. The paper provides information on their current applications, technical challenges, possible future applications, and outlook.

Optical and odor sensing nondestructive techniques

All the selected techniques for this review can be broadly classified into optical and odor sensing technologies. Optical techniques use selected portions of the electromagnetic spectrum as applied in NIRS, HSI, and MSI, whereas the odor-sensing techniques such as MOS and CSA employ chemo-responsive dye interactions with sample volatiles for monitoring of meat quality and safety. The characteristics, strengths, and weaknesses of the selected techniques are summarized in Table 1. The strengths of the various technologies have been explored in the context of realizing their potentials for the real-time monitoring of meat quality and safety.

Table 1. Summary of the characteristics of all the optical and odor sensing techniques under review.

Techniques	NIRS	HSI	MSI	E-nose based on MOS	E-nose based on CSA
Mode of sensing	Spectra	Spectra and imaging	Spectra and imaging	Odour (meat VOCs)	Odour (meat VOCs)
Sample portion covered by spectra/image	Small	Large	few selected spectra and images	N/A	N/A
Data size	Low	Large	Low	Low	Low
Technical know-how required for data processing and operation	high	Higher	Higher	Low	Low
Meat sample attributes predictable	Chemical biological physical	Chemical biological physical	Chemical biological physical	classification and discrimination	classification and discrimination
Unique strengths	Generates only spectra data that requires less data processing and handling	It generates spatial and spectra data; Capable of predicting more sample parameters	Few relevant spectra and image selected; faster data processing and efficiency achieved	low data size generated, hence rapid data processing	generates low data size to enable rapid processing
Distinct weaknesses	It has lesser sensitivity/lower depth of penetration; and unable to sense gaseous matter	Huge data generated, making data processing complex and slow	Few relevant spectra and images selected, lesser attributes can be predicted from such a data source	Its results are easily influenced by temperature and humidity, and possible leakage of MOS into sample (poisoning)	Selection of appropriate dyes for fabrication of sensor array is difficulty and tedious dyes printing

Electronic nose (e-nose); metal oxide (MOS); colorimetric sensor array (CSA); hyperspectral imaging (HSI);multispectral imaging (MSI); near-infrared spectroscopy (NIRS).

Near-infrared spectroscopy (NIRS)

The infrared region of the electromagnetic spectrum is divided into near-infrared, mid-infrared and far infrared. Although the mid-infrared and near-infrared have been applied as nondestructive spectroscopic techniques for meat quality and safety monitoring,[10–12] the former technique is less applied compared to the latter. Mid-infrared spectroscopy (MIRS) is underpinned by molecular vibrations that result from stretching, bending and rotational motions of the atoms in a molecule. Distinctively, the mid-infrared has poor sample depth penetration, less flexibility in terms of delivery, very good sensitivity, and produces clear and distinct peaks from which it is possible to identify molecules (chemical information) in soft meat tissues, but it has limitations for the determination of physical properties of samples.[13] However, near-infrared, which results from overtone and combination vibrations, has excellent sample penetration depth, highly flexible delivery, and is moderately sensitive while also generating spectra that contain chemical information as well as physical properties of samples.[14] The NIRS has therefore been selected and reviewed for the reason of having a broader nondestructive usage scope compared with the MIRS.

The NIRS is one of the most extensively reported optical techniques; it utilizes spectra information combined with algorithms for monitoring the characteristics of food materials like meat. Its ability to record the spectra of both solids and liquids make it very useful as a technique for the prediction of components of meat samples whose rheology and structure are quite complex. Its application as food analytical technique dates back to 1950s after its discovery by Herschel as reported by Porep et al.[15] However, the advancements in the use of this technique came along with the development of novel spectrometer configurations based on fiber optic probes and their combination with multivariate algorithms.

A NIRS system is composed primarily of a light source, beam splitter system, sample detector, optical detector, and data processing system (computer with installed data processing applications). It uses a source producing light covering the wavelength range of approximately 750nm to 2500nm of the electromagnetic spectrum, which is within the near-infrared wavelength[16,17]; thus, it is classified as an optical sensing technique. It is based on the principle that different chemical bonds in organic matter absorb or emit light of different wavelengths when a sample is irradiated. This makes it possible for the absorption bands within the NIR spectra collected from a meat sample to be related to specific functional groups of their constituent compounds in order to provide its quality and safety information.[17]

In general, NIRS has three modes of operation, namely reflectance, transmission, and absorbance. The reflectance mode is usually adopted for meat quality and safety. The operating procedure for NIRS comprises spectral data acquisition, spectral data preprocessing, calibration and prediction model development, and model validation.[16] An illustration of its setup is captured in Fig. 1

Nondestructive systems, including NIRS systems, are usually combined with multivariate algorithms to enable chemical information extraction from spectral data, for

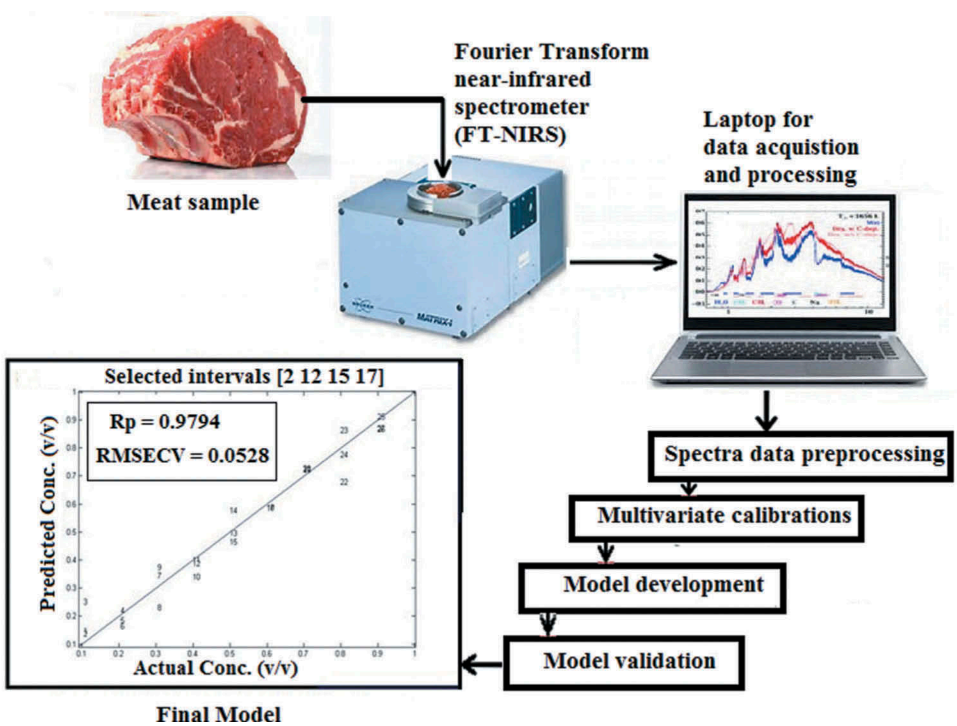

Figure 1. NIRS system setup for meat quality and safety monitoring.

spectra preprocessing to remove redundant information in the acquired spectral data as well as for model establishment towards the prediction of quality and safety traits of meat.[18] In terms of prediction model establishment, spectral data acquired from meat samples relevant to the targeted quality and safety variables are divided into calibration and prediction sets, where the former set is used for the building of models and the latter for the testing of the built models.[17,19,20] The performance of the built models for prediction is based on indicators such as the correlation coefficients of determination of the prediction set (Rp) and the calibration set (Rc), the root-mean-square error of prediction (RMSEP) and cross-validation (RMSECV).[21,22] Thus, the closer the Rp and Rc are to 1, and the closer RMSEP and RMSECV are to 0, the higher the performance of the model for the prediction of targeted meat quality and safety variable.[23] Combination of various algorithms with NIRS systems for the noninvasive prediction of the intrinsic meat quality and safety attributes is so crucial to the extent that reported works on NIRS are replete with them. Some algorithms that have been combined with NIRS systems and applied to pork, chicken and beef quality and safety prediction are summarized in Table 2. However, because the prediction performance of models for attributes may differ based on algorithms combined with the NIRS systems,[37] different types are tried and those that generate models of higher performance are selected. For instance, in the prediction of TVC (Total viable count) for the classification of food pathogens, more than one algorithm, namely linear discrimination analysis (LDA), k-nearest neighbor (k-NN), partial least square discrimination analysis (PLS-DA), support vector machine (SVM), back propagation artificial neural network (BP-ANN), and online sequential extreme learning machine (OSELM), were employed.[18] NIR spectroscopy has been applied in muscle food analysis based on its merits, which include increased operating speed, application possibility for in-line, on-line and at-line process monitoring.[38] The speed with which the data acquired via the NIRS are processed with these multivariate algorithms make their combination with the NIRS suitable for real-time monitoring of meat traits.

As regards meat quality and safety monitoring, considerable number of research studies have been conducted using NIRS combined with partial least square regression (PLSR) for the assessment of physical characteristics of pork such as pH, Warner-Bratzler shear force (WBSF) and cooking loss with Rp values of 0.82, 0.64–0.70 and 0.88, respectively, achieved.[39,40] Similarly, Rp value of 0.81 was realized for the prediction of pH of chicken breast using NIRS coupled to PLSR algorithm.[41] However when NIRS was combined with PLSR and canonical correlation analysis (CCA) for the determination of chemical composition of pork fatty acid (FA) composition, IMF, protein, dry matter, ash, phosphate, moisture, water activity, gross energy, NaCl, carbohydrate and calcium, Rc/Rp values ranging from 0.60 to 0.99 were obtained.[39,42,43] Rp values obtained from models built using data acquired via NIRS combined with different algorithms for the prediction of meat quality attributes may vary according to quality traits being monitored. Thus, to improve the prediction of quality attributes, different algorithms must be tested and the most efficient selected. For instance, when NIRS was combined with SiPLS and applied to the determination of total viable count (TVC) and total volatile basic – nitrogen (TVB-N) in pork, Rp value of 0.95 and 0.80 were, respectively, obtained[18,36]; however, when combined with PLS-DA for the classification of tenderness and breeds, Rp values of 0.61 and 0.95, respectively, were achieved.[17] This indicates that the NIRS combined

Table 2. Some selected NIRS applications to beef, pork, and chicken quality and safety monitoring.

Type of study	Property	Model calibration	References
Qualitative analysis	Color of pork and beef	PLS, SVM	[24–26]
	Detection of spoilage in intact chicken breast muscle	OPA, PCA, PLS-DA	[27]
	Discrimination of pork storage time	LDA, KNN, BPANN	[28]
	Classification of pork loins for tenderness	PLS-DA	[29]
	Pseudomonas spp identification in chicken	PCA, BP-ANN	[30]
	Discrimination of enhanced quality pork	PLS-DA	[31]
	Classification of beef carcass and chicken breast fillets based on pH	PLS-DA, PCA, PLSR	[32,33]
	Adulteration detection in minced beef	SIMCA	[34]
	Classification of food pathogens	LDA, KNN, PLS-DA, SVM, BPANN, OSELM	
	Classification of broiler breast based on measurements of WHC	LDA, PLS-DA	[35]
Quantitative analysis	Predicting fatty acid profile in chicken breast	MPLS	[36]
	pH of pork and beef	PLSR, GA	[26]
	Prediction of glycogen and water content of fresh pork	GPLS, PLS, PCA, PLSR, MLR	
	Moisture, fat, ash and protein content of beef	PLSR	[10]
	FA composition of pork carcasses	PLS	[29]
	IMF content of pork	PLS	[29]
	Fat content of beef and pork	PLS	[29]
	Protein content of pork	PLS, CCA	[29]
	Predicting chicken quality attributes (pH, WHC)	PCA, PLSR	[27]
	TVB-N and TVC of pork	SiPLS, PLSR	[26]

with PLS-DA gave a high prediction for the pig breed types but proves unreliable for monitoring the tenderness of pork.

Apparently, the low Rc/Rp values in most cases are attributable to the homogeneity and the nature of the samples in relation to the parameter being determined. In the determination of the chemical components of samples, ground or minced meat samples (homogenized) are reported to yield better results. De Marchi et al.[35] reported Rp values lower than 0.6 during FA profile determination using an intact chicken breast. Conversely, higher values Rp were obtained for qualities derived from the muscle structure such as WBSF, firmness, tenderness, water holding capacity[24,42], in which case samples used were not minced or ground. This clearly shows that in the determination of the chemicals components of meat, ground samples allow chemicals present in the meat matrix to be released and made available to enable their spectral information acquisition to achieve higher Rp values; whereas, in the case of physical qualities, better Rp values are realized by maintaining the integrity of the meat sample's structure. Thus, the sliced or minced samples employed in prediction of WBSF may have accounted for the relatively lower Rp values of <0.72 reported by Liao et al.[39]

With regards to the physical attributes of chicken, pork, and beef, some have been well predicted in recent years. Also, meat chemical composition, quality attributes such as FA composition, which has assumed an utmost importance for the provision of feedback to meat producers and animal feed industry during animal breeding and meat content screening for desirable fat quality, can be predicted.[44] For meat microbial properties, TVC and TVB-N have been monitored in pork, beef, and chicken with high predictability as freshness indicator. Various qualitative studies which encompass classification of meat based on the use of attributive characteristics such as meat freshness, tenderness, color, and microbes present[45–47] have been conducted with the use of NIRS combined with multivariate algorithms with remarkable successes achieved. Table 2 provides some NIRS applications on quality and safety attributes as applied to pork, chicken, and beef. Table 2 groups some of the quality and safety attributes of chicken, pork, and beef that have been monitored using NIRS combined with various multivariate algorithms into those that were quantified and classified with respect to algorithms used. This, therefore, shows that the algorithms combined with NIRS are selected based on whether target meat quality and safety attributes are to be used to classify or quantify meat samples or their contents.

The results of the studies carried out on pork, chicken and beef quality and safety revealed that NIRS combined with efficient multivariate algorithms possess a high potential for real-time application based on its lower spectra data size and handling techniques compared to other optical techniques like HSI, hence lesser operating time, which is necessary for real-time monitoring of meat. It is also used simultaneously to determine multi-attributes of meat quality and safety.[42] However, its spectra cover only a small surface of the sample and hence, generate low spectra size data that may not contain information relating to the prediction of some of its chemical attributes. The development of fiber optic probes with broad scanning surface may allow for the collection of representative spectra from the meat samples for possible prediction of most quality and safety attributes. In addition, NIRS inability to predict the external features of meat samples could be addressed by merging it with imaging devices capable of capturing spatial information as well as multivariate algorithms to integrate both spectral and spatial data for the possible monitoring of both internal and external quality and safety attributes of chicken, pork and beef simultaneously and on real-time basis.

Hyperspectral imaging (HSI)

Optical sensing technique such as NIRS spectroscopy is unable to acquire spatial information for nondestructive evaluation of meat and its products. However, hyperspectral imaging presents itself as a unique all-in-one approach towards the acquisition of both spatial and spectral data,[48–50] serving as a richer source of information for the evaluation of meat quality and safety. Hyperspectral imaging technique has emerged as a powerful analytical tool for nondestructive quality assessment of food and agricultural products,[51–54] although it was originally developed for remote sensing.[55,56] Hyperspectral imaging system integrates hardware and software platform for conventional imaging and spectroscopy to obtain both spectral and spatial information from chicken, pork and beef samples simultaneously.[56–59] The spectroscopy component detects or quantifies meat chemical quality and safety attributes such as intramuscular fat (IMF), fatty acids (FA), protein, and TVB-N, based on acquired spectral signatures as well as other traceable physical qualities resulting from biochemical reactions within meat samples such as color. The imaging component captures the spatial information, which provides details on the physical quality and safety attributes of meat samples such as color, texture, and tenderness.[58]

HSI system consists of a camera, spectrograph, illumination units, translation stage, and a computer equipped with imaging acquisition software. An illustration of the HSI with a three-dimensional image “hypercube” comprising two spatial dimensions and one spectral

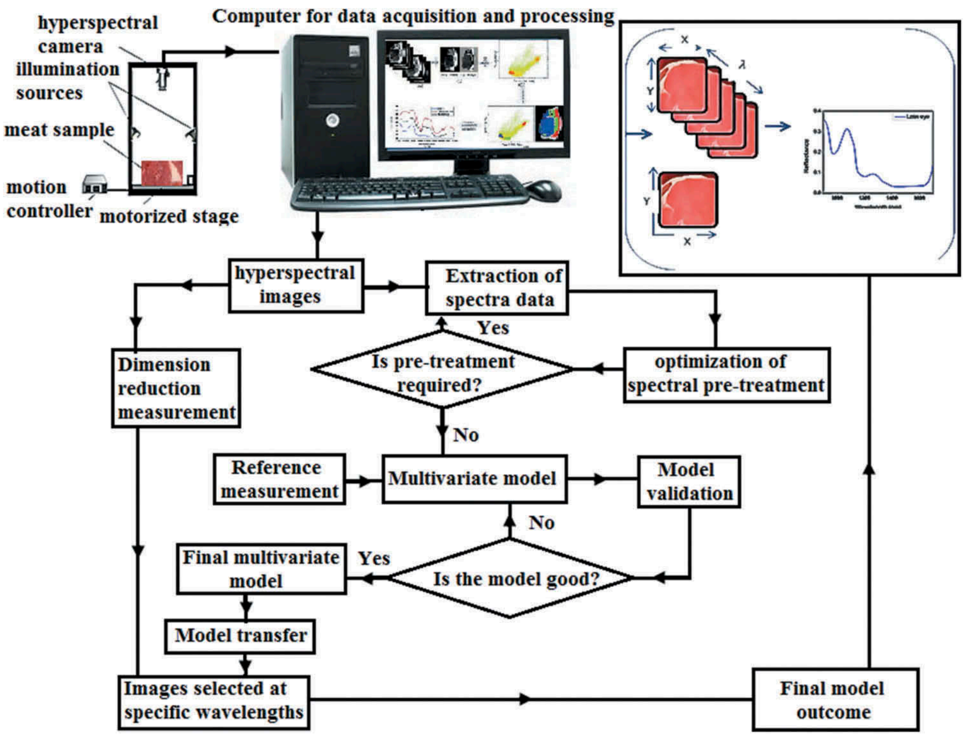

Figure 2. Hyperspectral imaging system and schematic processing for meat quality and safety monitoring.

dimension and hyperspectral images processing flowchart is shown in Fig. 2. A typical meat sample's hypercube data shows its biochemical constituents segregated into distinct areas of the image, such that regions of the meat with similar spectral properties have similar chemical composition.[52] Spectral and spatial information on the target quality and safety attributes are contained in the HSI hypercubes. The regions of interest of target components are selected from them and their corresponding spectra extracted for preprocessing and subsequent development of prediction models using different multivariate algorithms.

Generally, after the hyperspectral images are acquired, various variable selection methods such as successive projection algorithm (SPA), uninformative variable elimination (UVE), Genetic algorithm (GA), stepwise procedure and regression coefficients from the PLS model are used to screen critical feature wavelengths,[60] corresponding to their single-wavelength images. Subsequently, the image-textural features are then extracted with methods like grey level co-occurrence matrix (GLCM), wavelet decomposition and semivariogram analysis.[12,61] These variables obtained from the spectra and images of textural features extracted are often combined and correlated with values measured by the physico–chemical experiments for the developing of models. Results of comparative tests carried out have revealed that the combination of these fused variables, which are composed of spectral and textural features from grey level gradient co-occurrence matrix (GLGCM), obtained via HSI had higher potential for meat quality evaluation as obtained results for spectral, texture and their combined data yielded Rp values of 0.783, 0.583, and 0.794, respectively.[62] This ultimately corroborates the fact that different algorithms combined with the hyperspectral system may yield different model performances. In addition, hyperspectral scattering technique, which has become increasingly popular for meat quality evaluation, was explored using Lorentzian function (a and b) and Gompertz function (α, β, ε, and δ) to interpret the scattering profiles. Results showed good fitting performance especially for Lorentzian parameter b and Gompertz parameter β.[63] This suggests the spectral mode settings of the system may greatly influence data collected, which in turn can affect the performance of prediction models developed from them for meat quality and safety monitoring.

Hyperspectral systems combined with different chemometric algorithms have been applied at experimental levels in monitoring the quality and safety of pork, beef, and chicken based on classification and quantification tasks of multiple physical properties. For instance, physical properties such as color, pH, drip loss, cooking loss, WBSF, marbling and freezing temperature for pork and beef were predicted using different chemometric algorithms with Rc/Rp values ranging 0.81–0.93, 0.73–0.87, 0.71–0.85, 0.86–0.96 and >0.83, respectively,[64,65] and chemical properties such as IMF, moisture, NaCl, water activity, protein, and fat were predicted with Rc/Rp values >0.93, 0.87–0.94, 0.92–0.93, >0.91, >0.92 and >0.95, respectively.[56,66] Microbial properties like TVC, psychtrophs plate count (PPC) and *E. coli* were correspondingly predicted with Rc/Rp values range of 0.83–0.94, 0.89, and 0.94, respectively.[48,58,67,68] The Rc/Rp recorded for the afore-stated reported works were sufficiently high to enable their use for monitoring the respective quality and safety attributes in chicken, pork and beef monitoring. However, those attributes with Rc/Rp <0.85 could further be improved with more efficient algorithms to enhance the robustness of built models for their prediction. Also, HSI has been used for the classification of meat grades such as red meat species with Rc/Rp values ranging from 0.88 to 1.00 obtained[58,69,70] as well as the prediction of fresh and frozen-thawed meat, and fat portions from inner and outer subcutaneous layers with remarkable Rc/Rp values of 1.00 and 0.95,respectively.[71,72] In addition, Naganathan et al.[73] used the gray level co-occurrence matrix features extracted from the hyperspectral image of beef carcasses to build models that achieved a meat tenderness certification accuracy of 0.876 (87.6%), which was used successfully to classify beef samples. The same author predicted the age of tenderness of cooked beef with HIS with an accuracy of 0.867 (86.7%).[74] In addition, studies conducted on physical properties like grades of pork based on species, and the discrimination between fresh and thawed pork samples yielded Rc/Rp values in the range of 0.88–1.00 and Rc/Rp value of 1.00, respectively,[70,71] when the pork samples were kept intact. In addition, various studies on pork have reported the visualization of moisture distribution in each pixel of the hyperspectral image, moisture evolution and migration in pork slices[75]; as well as salt content distribution by converting the quantitative models into image pixels to display salt uptake in pork slices at different salting periods.[76] These two latter studies demonstrate that hyperspectral images contain vital information that can be extracted with chemometric algorithms for the prediction of meat quality and safety attributes. In addition, these images provide a detailed spatial distribution of the visual quality and safety information in the form of mapping the various constituents of meat sample, hence it is a promising method capable of being used for the prediction of meat quality.[77]

The HSI combined with chemometric algorithms has a superior advantage as regards its ability to provide rich spectra and spatial information from its hypercubes, with which the intrinsic quality and safety attributes of chicken, pork, and beef such as their chemical components and microbial activities are predicted. This capability of HSI being able to churn out rich spectral and spatial information makes it quite unique for the quality and safety monitoring of meat. However in its current form, the system lacks the ability to be used for real-time quality and safety monitoring because it is not portable, it is very expensive, and it churns out large data size making data processing very cumbersome and time-consuming. For its potential to be improved for real-time quality and safety monitoring of chicken, pork, and beef, the development of hardware devices and software applications for large data processing with speed are required, a prerequisite for achieving real-time applicability. In the event that these provisions are made in HSI systems, its potential for real-time monitoring of meat quality and safety could be pragmatically realized in the meat industry.

Multispectral imaging (MSI)

Multispectral imaging (MSI) combines spectroscopy with imaging for quality and safety monitoring of food samples. The major challenge in the meat industry in contemporary times is obtaining fast and reliable information on meat quality and safety from the production line until it gets to the ultimate consumers.[55,78–81]

Although there are several emerging nondestructive techniques, there is a crucial need for a nondestructive technique that has the potential of evaluating simultaneously multiple internal and external qualities of meat with speed, at a relatively lower cost, and that provides reliable data for its possible online application in the industry.[82,83] Multispectral technique serves as a solution to the constraints of both NIRS and HSI as nondestructive optical techniques capable of combining spectroscopy and imaging properties to predict chemical, biological, physical and sensory attributes among others meat quality and safety attributes on real-time basis due to the low spectra and image data size used.[80,84] These attributes have enabled its deployment as a reliable and rapid nondestructive technique for real-time application in the meat industry. For instance, NIRS can only provide spectral information to predict attributes relating to the internal components of meat but lacks the ability to predict some physical attributes; this creates a deficit in its usage as far as quality and safety issues are concerned. On the other hand, HSI combines the merits of both imaging and NIR spectroscopy by capturing both spatial and spectral information from samples for quality and safety monitoring; however, it cannot be used online because of its huge data size generated, which requires a long span of time for handling and processing.[85,86] This time span is significantly decreased by reducing the high dimensionality of the hyperspectral images to build a multispectral imaging system consisting of a few critical spectral wavebands for specific applications.

The multispectral imaging system integrates imaging with spectroscopy to produce comparatively less spectral data, which enables fast processing, hence making it suitable for online application for meat quality and safety evaluation.[55] It combines visual and near-infrared wavelengths to assess both spatial and spectral information on objects of interest with few discrete spectral images, which makes data handling easier and the cost of the system comparatively lower, thus offering the possibility of it being used for real-time food monitoring.[87] In addition, it has also been reported to perform better than colorimeter in assessing meat color.[88]

MSI has been explored as a nondestructive and rapid technique in monitoring the microbial quality of minced pork at different thermal conditions during their aerobic storage with Rp value of 0.80 recorded.[89] MSI for continuous frying quality of meat resulted in Rp value of 0.95.[90] Its use for the detection of change in meat color during storage gave Rp/Rp values in the range of 0.91–0.80.[91] In addition, its application to L*a*b color prediction of different types of raw meat as an indicator for quality monitoring has been reported with Rc/Rp value ranges of 0.86–0.93, 0.86–0.96 and 0.64–0.84 respectively.[92] MSI had been reportedly deployed for the classification of beef quality based on TVC with the resulting Rc/Rp values ranging between 0.78 and 0.93.[93] For identification of water-injected beef (beef injected with water to increase its weight for profiteering), Rc/Rp values in the range of 0.92–0.95 were obtained.[94] Also, it has been applied to detect adulteration in minced beef and pork with high Rp values ranging between 0.97 and 0.98.[80] For quantitative prediction of total TVB-N pork, Rp value of 0.89 was realized[95], whereas Rp value of 0.90 was obtained when used for the prediction of cooked beef tenderness.[96] The sufficiently high Rc/Rp values recorded in the various reported studies were based on combining MSI with different algorithms to improve the predictability of the various attributes. As a result, its performance can be affected by the efficiency of chemometric algorithms used for the extraction of the few selected spectral images needed for developing the prediction models.

Although MSI is able to combine spectral and spatial information towards rapid prediction of quality and safety attributes of meat, and is thus capable of being deployed for real-time quality and safety monitoring, it comes with its own limitations. For instance, because only few spectral images of interest are used, the range of quality and safety attributes that can be predicted is very narrow. However, this can be addressed by the development of hardware, software applications, and efficient chemometric algorithms that can allow for the processing of huge spectral and spatial data simultaneously and instantaneously to enable its use for real-time quality and safety monitoring in the meat industry.

Electronic nose (e-nose)

E-nose can be appropriately classified as a nondestructive odor sensing electronic device (NOSE) that mimics the human olfactory system.[97] E-nose, unlike the optical techniques, employs the use of sensors that are capable of detecting smell produced from volatile organic compounds (VOCs) in food materials for their quality and safety prediction. Likewise, e-nose employs sensing elements such as quartz crystal microbalance (QCM), bulk acoustic wave (BAW), metal oxide sensors (MOS), and colorimetric sensor arrays (CSA) composed of chemo-responsive dyes.[98–101] The most used type of odor sensing elements in e-nose are metal oxide sensors, and recently the colorimetric sensor array has been introduced and applied as a solution to the constraints of the former.

The MOS e-nose systems detect complex volatiles through the use of cross-sensitive metal oxide sensor arrays. MOS-based e-nose, just like all e-nose techniques, is low cost, fast, and reliable, nondestructive, and portable, as such, it has been reported to be a promising technique for the evaluation of food properties.[102,103] There are various types of commercial and experimental based MOS e-nose systems that have been used for the purpose of carrying out research.[99] For instance, a commercial sensor composed of sampling apparatus, a detection unit containing MOS arrays and pattern recognition software was used for the analysis of pork adulteration in minced mutton with Rc/Rp values ranging from 0.91 to 0.99 for various chemometric algorithms.[102] Also, a laboratory-based e-nose system, which was designed and developed by the Agricultural Product Processing and Storage Laboratory of Jiangsu University, was made of a gas bottle, gas filter, flowmeter, vacuum pump, flow valves, MOS arrays, and computer with pattern recognition software installed. This e-nose was combined with different algorithms and used for monitoring of the fermentation process of animal protein feed with Rp values ranging from 0.91 to 0.97 achieved. As well, analysis of the VOCs in pork samples yielded an Rp value of 0.95.[104,105] A diagram illustrating the setup of the MOS-based e-nose is shown in Fig. 3.

The sensing system and pattern recognition system are two main components of an e-nose that must be present whether it is a commercial or experimental type. In the MOS e-nose, tin dioxide (SnO_2) doped with a small amount of catalytic metals like palladium or platinum are reported to be one of the widely used although oxide-based metals such as zinc oxide (ZnO_2), titanium dioxide (TiO_2) and tungsten oxide (WO_3) as well as titanium-substituted chromium oxide, have been found to be of improved performance with respect to their relative humidity variations.[106] In addition, the use of an appropriately selected pattern recognition component in any e-nose system is relevant to improving the sensing performance of the system. In this regard, chemometric algorithms combined with the e-nose systems aid the building of models that are used in classifying the food materials based on their emitted odor. However, the efficiency of one chemometric analytical tool may vary from another when applied to the same sample.[99,107]

Although metal oxide sensors employed in e-nose respond to a wide range of VOCs, they tend to have higher sensitivity for some compounds than others. For instance, they have higher sensitivity for aldehydes, alcohols, and ketones compared with terpenes and aromatic compounds. However, varying the operating temperature of the metal oxide

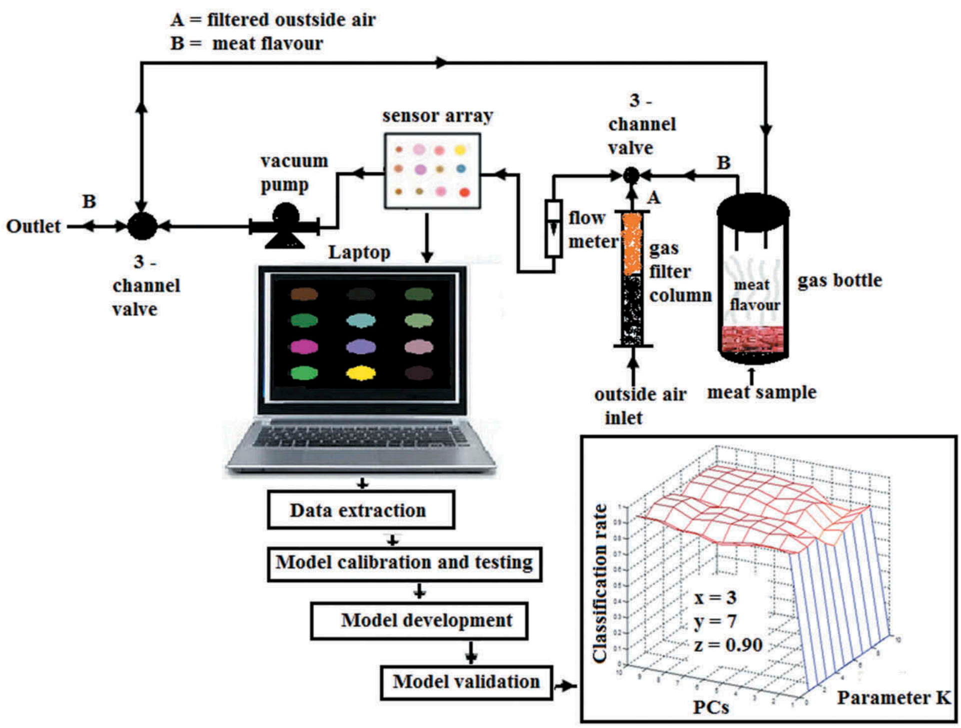

Figure 3. MOS-based e-nose system setup illustration for meat quality and safety monitoring.

sensors presents an option for increasing their selectivity and sensitivity for different VOCs.[106] This is because a rise in temperature increases the rate of reactivity of the MOS with the gases (volatiles); whereas a decrease in temperature causes the reverse.

Although many studies have been conducted on MOS-based E-nose, this technique is still at the experimental level and can only be migrated to industrial level if constraints that affect its performance such as temperature drift, humidity influence, sensor redundancy, and sensor poisoning are addressed.[108,109] The humidity effect occurs because the metal oxides which are the constituent dyes used in the MOS systems are hydrophobic. Attempts to solve these problems by combining semi-conducting chemical sensors and other gas sensors that use more than one sensor in their array systems have led to complication in the nature of their sampling system.[98,99] The main challenge of MOS-based e-nose is the selectivity and independence of the sensors; this is because sensors with poor selectivity affect the discrimination power of the whole array of sensors employed in the e-nose system. In addition, there are no specific metal oxide sensors that have been manufactured and incorporated into e-nose as sensing elements for the detection of odor emitted by specific VOCs in food materials such as meat. Apparently, all the metal oxide sensors that have been used are cross-responsive to the VOCs they come into contact with. MOS-based e-nose has been deployed in areas of quality control, process monitoring, tracing of product geographical origin, authentication, and adulteration detection in many foods and other agricultural products.[102,110,111]

The CSA-based e-nose, just like the MOS e-nose, is always combined with appropriate chemometric algorithms for the discrimination, classification, authentication and adulteration detection based on odor that emanates from samples containing VOCs such as meat and meat products.[112,113] A remarkable difference in the CSA-based e-nose is the change in the sensing element from metal oxide sensor to a sensor array composed of chemo-responsive dyes. The diagram in Fig. 4 shows the setup of the CSA-based e-nose system.

The underlying principle of the CSA-based e-nose is that it is made up of different chemo-responsive dyes (sensor array) printed on the reverse face of silica gel plates, which are hydrophobic materials.[114] Upon exposure to the odor from the VOCs in a test meat sample samples to the metalloporphyrins (sensor arrays), they react to give unique color profile for each test sample, from which the differences in images captured prior to exposure to the VOCs emitted from the test sample and after exposure are obtained and subjected to multivariate analysis for quality and safety monitoring.[115] Though the sensor arrays are nonspecific to the VOCs within the meat sample, the odor emitted stimulates the generation of characteristic fingerprints representative of the chemical content of the VOCs released. This technique has therefore been used for the monitoring of agricultural products such as pork, chicken, and beef, which contain various VOCs and degrade with the passage of time as a result of microbial actions.[116]

The CSA-based e-nose, unlike the MOS e-nose, overcomes the challenge of humidity influence, which presents constraints in the latter.[115] The CSA, which constitutes the sensing unit of this type of e-nose, helps to visually identify a broad range of ligating vapor molecules and exploits the advantage of the color changes induced in metalloporphyrins upon ligand binding to produce a peculiar signature or fingerprint for each analyte. The hydrophobic nature of the material on which the sensor array is printed prevents water vapor from influencing its performance.[114,117] In addition, it is reported to be relatively

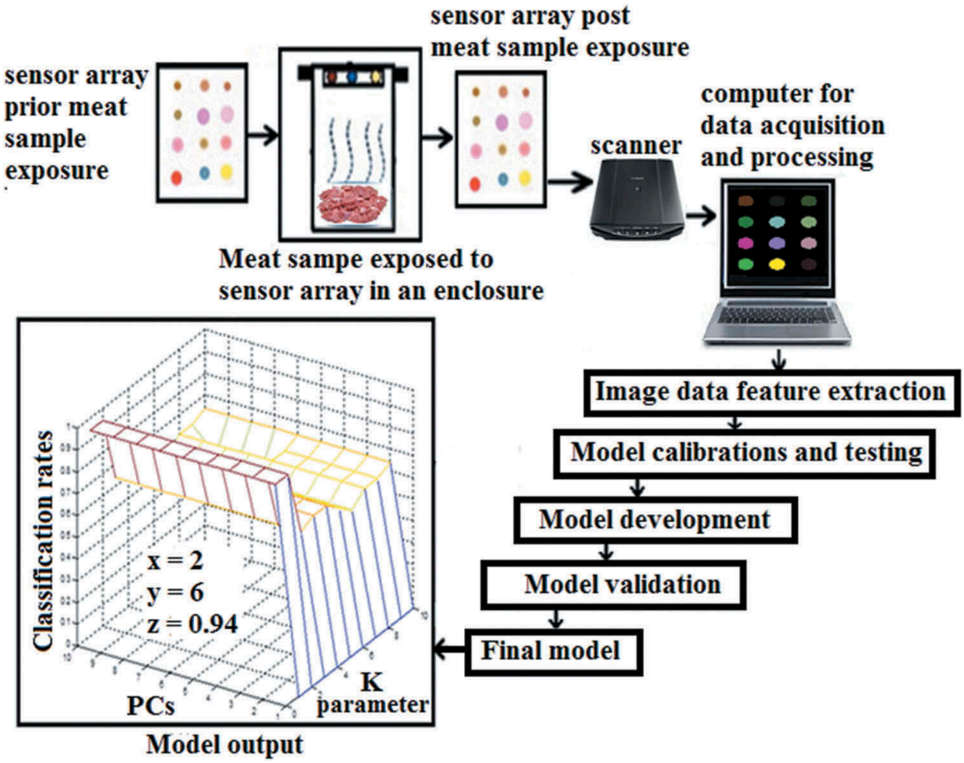

Figure 4. CSA-based e-nose system setup illustration for meat quality and safety.

cheaper, minimizes signal-transduction, and overcomes the humidity problems associated with the MOS-based e-nose.[25]

Chemometric algorithms, as usual, are very crucial to obtaining high performance from models developed based on the use of CSA e-nose techniques. For instance, because the spoilage of meat is a complex process, a single linear algorithm may not adequately establish the relationship between the VOCs generated by the microbial actions on the meat sample and the colorimetric sensor array present in the CSA e-nose system. Therefore, in monitoring the spoilage of chicken, nonlinear chemometric algorithms such as backpropagation artificial neural networks (BPANN) and backpropagation – adaptive boosting (BP-AdaBoost) were observed to yield Rp values of 0.78 and 0.81, respectively, and showed superior performance to linear chemometric algorithm like PLS (Rp = 0.59).[115] In addition, the support vector machine (SVM), a supervised learning technique having the advantages of aiding with good generalization, reducing the tendency for over-fitting, simultaneous minimizing model dimensions and estimating of errors, was combined with CSA-based e-nose to classify beef fillets into three sensory classes based on different storage temperatures with good model performance realized (Rp = 0.89).[27] The total viable counts (TVC) in chilled pork was also predicted using a CSA-based e-nose combined with SVM and PLS, where principal components analysis (PCA) was used to cluster the e-nose data acquired, and a model was developed with SVM and PLS to establish the correlation between bacteria loads and the e-nose signals that yielded

Rc/Rp values in the range of 0.88–0.94.[28] The cited studies support the import of chemometric algorithms combined with CSA-based e-nose systems toward their application to the monitoring of meat quality and safety. CSA-based e-nose systems that employ the use of sensor arrays of chemo-responsive dyes as their sensing elements are relatively new and therefore, have been deployed in only few research studies for the monitoring of the quality and safety of pork, chicken, and beef. That notwithstanding results from the studies reported on their applications have demonstrated their superiority to the MOS-based e-nose as a result of overcoming the humidity influence that significantly affects the quality and safety results of test samples. For instance, the CSA e-nose was combined with algorithms such as orthogonal linear discrimination analysis (OLDA), adaptive boosting (Adaboost), Adaboost-OLDA and back propagation artificial neural networks (BPANN) in evaluating the freshness of chicken based on the TVB-N values resulting in very high classification performance of Rc and Rp = 1.00.[29] This thus demonstrates the high potential of using the CSA-based e-nose combined with classical algorithms for the evaluation of chicken freshness. The performance of the various models developed by combining the CSA-based e-nose technique and the respective algorithms demonstrate a strong potential for its deployment for real-time quality and safety monitoring of meat in the meat industry.

Although the MOS system has the unique challenge of being influenced by humidity, which is addressed by the CSA-based e-nose, both systems are constrained in the sense that the sensor arrays deployed in these two systems are all cross-reactive sensors. There are challenges involved in fabricating sensor arrays for the e-noses as it requires tapping from the pool of experience and available literature, as well as trial-and-error approach, which oftentimes results in chemo-dye wastage and being time-consuming in printing them on the reverse face of cut silica plates employed in the CSA e-nose systems. However, this can be addressed with the development of more specific or universal sensors whose reactions to various meat components can easily be identified and the use of quantum chemistry computations to theoretically selected possible sensitive chemo-dyes to VOCs,[30,111] in meat samples.

The MOS and CSA e-noses application to meat quality and safety have so far met with remarkable successes via using the odor emitted from samples to determine their state of freshness or otherwise, which hitherto was done by humans sense of smell. The use of human sensory for meat quality and safety analysis based on odor of meat samples is quite laborious, limited to small-scale production and also prone to error. Unlike HSI, MSI, and NIRS, the e-nose techniques generate the lowest data size and therefore, reduce handling and processing time to enable their application to real-time meat quality and safety monitoring.[27] Moreover, their low cost, reliability, rapidity of obtaining results, portability, and simplicity make them potential instruments for monitoring meat quality and safety on a real-time basis.

Integrating multi-sensors for data fusion

Nondestructive techniques such as NIRS, HSI, MSI and the different types of e-nose (MOS and CSA based) possess numerous benefits as tools for meat quality and safety monitoring such as being nondestructive and fast. They produce reliable data, at a low cost, require little or no sample preparation, are less time-consuming and have the potential for online detection applicability.[57,104] Despite these general benefits, each of the nondestructive techniques has its own strengths and weaknesses in terms of their use for meat monitoring. A single technique may not fully cover all the various attributes needed for the evaluation of meat quality and safety.[31] Since the quality and safety of meat dynamics are complex and associated with varied attributes consisting of both external (physical properties – color, smell, texture, tenderness, etc.) and internal (chemical composition) characteristics, it is expected that in an integrated system, as one system aids the detection of the internal attributes, the other also captures the external ones in order to enhance the collective predicting performance of the integrated systems.[104] For instance, because HSI and e-nose techniques independently cannot identify the volatile organic compounds (VOCs) released and odor emitted from meat such as pork during spoilage, these two techniques were integrated to harness their collective strengths for the measurement of TVB-N of pork to evaluate its freshness.[21] The speed of data processing of these two integrated techniques increased as a result of abandoning the large spectral information and just selecting a few dominant hypercubes for analysis.[32] Also, data on color, texture, chemical composition, and smell of pork during spoilage was collected using nondestructive techniques such as NIRS, computer vision (CV) and e-nose, and were subsequently fused for the evaluation of pork freshness. Outcome from the fusion of the aforementioned techniques yielded a positive synergy as their collective model performance gave higher (Rp = 0.9527) compared to those of the individual systems (Rp = 0.630, CV; Rp = 0.649, e-nose; and Rp = 0.8761, NIR).[104]

Although data obtained on food quality and safety monitoring from one or more instruments and approaches have been handled in various studies, only a few studies exist on the combination of data from dissimilar instrumental techniques for the evaluation quality of meat such as pork and beef chicken. The combination of data from different types of systems can be quite difficult and requires the need to understand the merits and demerits derived specifically from each system as well as establish when there is a case of redundancy in the collected data from the different complementary applications.[33]

In integrating two or more techniques for the evaluation of meat quality and safety, data from the integrated techniques are fused at three different levels. These are low-level fusion (LLF); intermediate or mid-level fusion (ILF/MLF); and high-level fusion (High-Level Fusion) with each level serving specific functions.

The LLF involves the concatenation (row by column arrangement) of data obtained from the samples into a single matrix that contains as many rows of samples analyzed; with their signals (variables) measured by an integrated nondestructive system placed in columns. These thus become the source data from which a final single prediction or classification model is developed representative of the fused data. In addition, a three-dimensional merged data matrix is constructed that consists of the number of samples as the first dimension, the signals obtained from the samples using the individual instruments integrated as the second dimension, and the products of the sample number and their corresponding signals obtained from the instruments as the third dimension. This matrix is then subjected to an appropriate multivariate method for analysis, for example, a stepwise variable selection was done at LLF with multivariate methods such as PCA, LDA, and PLS in the detection of adulteration of turkey meat in minced beef with Rp of 0.95–0.99 achieved.[26]

With regards to ILF/MLF, essential features are extracted from each of the data sources individually and then arranged into a single array. This array is subsequently used for multivariate classifications and predictions. ILF/MLF involves the fusion of a number of latent variables obtained independently from the signals of each of the instruments integrated. For instance, PCA was used for the extraction of feature variables containing information on external attributes (color, texture, smells) and internal chemical composition (carbohydrate, protein, and fats) of pork sample from NIRS, CV and e-nose separately with the resulting model performances (Rp values) of 0.88, 0.64 and 0.65, respectively, obtained. These were then fused at ILF for building a model to evaluate the freshness of pork whose performance yielded Rp value of 0.95, and thus demonstrated its superiority to the results obtained from the individually fused systems.[104]

HLF, referred to as the decision level fusion, involves developing independent classification or regression models computed from each of the data sources. The models from each data source are then combined into one model, which becomes the final model used for the evaluation of sample quality and safety. A simulation study performed to show the fusion of two data sets at HLF using Bayes classifiers revealed an improved model predictive performance of the HLF fused data sets over the individual data sets with lower error rate recorded for the former.[34]

The use of data fusion emanated from the exploitation of the weaknesses and strengths of two or more techniques toward enhancing the predicting performance of models developed from the integrated systems. With regards to monitoring meat quality and safety, data fusion has been applied in a fewer number of studies as opposed to the other techniques probably due to its relative recent emergence. However, these few studies have all confirmed data fusion as a strategy for meat quality and safety superior to the independently used and known nondestructive techniques. For example, in a study to detect the TVB-N content of pork, hyperspectral imaging and colorimetric sensor techniques were independently combined with PCA-BPANN to develop models for each individual technique, with Rc/Rp values of 0.573–0.622% and 0.741–0.762%, respectively, obtained.[21] However, when the two systems were integrated and combined with the same model calibration algorithm, the resulting model yielded Rc/Rp values of 0.805–0.820%, which revealed a significant improvement over the results obtained for the independent techniques, thus demonstrating the superiority of the data fusion technique to the individual techniques fused. Interestingly, when the two independent systems were integrated and combined with Adaboost algorithm, the Rc/Rp values yielded 0.932–0.939% as compared to that of PCA-BPANN algorithm (Rc/Rp values 0.805–0.820%). This showed that the integrated systems combined with Adaboost produced a significantly improved model for the detection of the TVB-N to the combination with PCA-BPANN. This presupposes that the selection and combination of an appropriate algorithm with the integrated system can improve the performance of the model developed towards the monitoring of meat quality and safety. A similar study compared the detection of TVB-N using MOS-based E-nose and NIRS independently as well as the integration of both techniques all combined with BP-ANN algorithm, which built models that yielded Rc/Rp values of 0.6495–0.8408%, 0.8761–0.9352%, and 0.9392–0.9586%, respectively.[104] This study also corroborates the fact that data fusion technique gives rise to superior models with higher Rc and Rp values compared to the independent techniques integrated.

Almost all the studies reported on the application of data fusion techniques to meat quality and safety monitoring revealed superior performances in training and prediction models developed for the integrated systems as opposed to those obtained from the individual techniques integrated. This confirms the positive synergistic effects derived

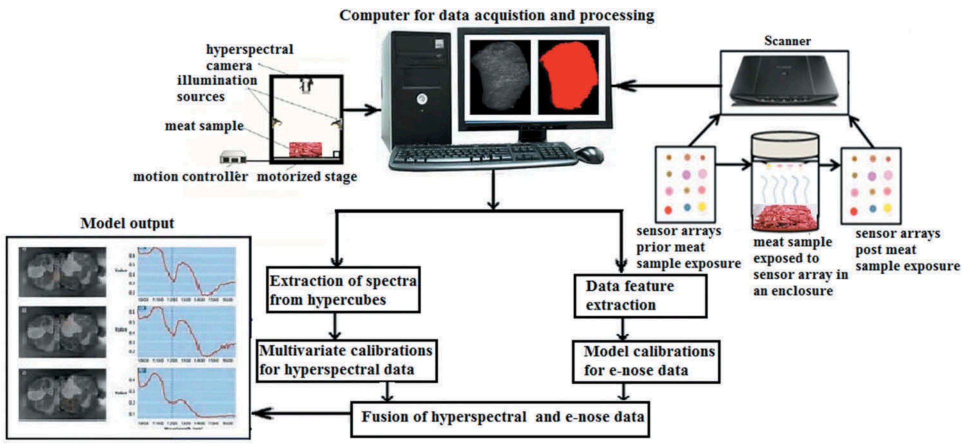

Figure 5. Diagram illustrating the multi-sensor integration for data fusion.

from harnessing the strengths of the independent techniques for the enhancement of the performance models of the integrated system. As a result of the improved performance of models developed via data fusion, it has high potential applicability for meat quality and safety monitoring. A diagrammatic illustration of the possible setup of multi-sensor integration for data fusion is shown in Fig. 5.

Technical challenges and future outlook

During the past two decades, considerable effort has been made to explore the possibilities of applying the optical nondestructive techniques such as NIRS, HSI, and MSI, and odor-sensing techniques like MOS-based and CSA-based e-nose to monitor meat quality and safety. Observed trends from literature reveal that these nondestructive techniques are fast gaining ground in the area of meat quality and safety monitoring due to their enormous benefits.

Various studies point to the fact that multispectral imaging (MSI) has emerged as a result of overcoming the constraints of both NIRS and HSI. MSI, however, obtains fewer spectra data and therefore its data processing is relatively faster for deployment for real-time monitoring of the quality and safety of pork, chicken, and beef even though it also has the limitation with respect to not having rich spectra data to predict a wide range of meat quality and safety indicators. Moreover, because the HSI generates a huge and rich source of spectral data that contain valuable information on the chemical composition of meat sample, there have been attempts to use it to extract data obtained from samples and then fuse them with data obtained from other techniques to help with the monitoring of quality and safety of meat samples. As a result, the fusion of data from different non-destructive techniques evolved for improving the collective model performance for monitoring samples quality and safety indicators.

The e-nose techniques also emerged as a way of mimicking the human olfactory system to help reduce the inconsistencies and subjectivity with regards to human panel discriminating of samples via sensory analysis. The various literature reviewed indicates that the MOS e-nose is the most widely used. The CSA-based e-nose is relatively newer than MOS and thus has been applied in lesser number of studies, more on fruits than on meat quality and safety evaluation. The challenge of humidity drift is still prominent in the MOS e-nose techniques, which ultimately influences the performance of models developed for discriminating meat samples but that has been addressed by CSA e-nose. These two types of e-nose are easily built in the laboratory and considerable efforts are being made to improve on their sensitivity and selectivity towards samples, which ultimately holds a lot of promise for future application to quality and safety monitoring on real-time basis.

Exploitation of the synergy of these analytical techniques via data fusion proves capable of yielding better prediction of meat quality and safety attributes compared to independent techniques. Because there are several meat quality and safety attributes, measuring or predicting each attribute and combining their acquired data ultimately lead to the provision of comprehensive information on meat quality and safety. Each technique may have its strengths, and a higher precision for capturing one attribute more than others. Harnessing their strengths via data fusion will likely yield an overall better quality and safety information on meat. That notwithstanding, sensor integration has its own challenges. There is a high cost involved in acquiring individual systems to be integrated. In addition, their data fusion data handling and processing require high-level technical skills. Developing simple and fast algorithms to aid the fusion of data from different systems as well as fabricating one-in-all systems is expected to provide a solution to these challenges.

The development of these emerging nondestructive techniques has been accompanied by the application of improved computer hardware processing power and data processing algorithms development in the area of meat quality and safety monitoring. Hence, data processing algorithms have become valuable throughout the entire value chain of the meat industries. The general trend seems to point toward searching for rapid and reliable methods for nondestructive detection of meat quality and safety throughout the production process in order to optimize production cost-effectiveness and to guarantee meat product quality and safety in all aspects. The potential savings, reduction in time and cost, and the environmentally friendly nature of the techniques discussed to make them the most attractive techniques with a bright future for real-time sensing of meat quality and safety.

The major barrier for the application of these advanced tools in the meat industry is the cost constraints. Although NIRS instrument has been applied for the measurements of several meat quality traits in an industrial environment and implemented for regular use, these analytical tools are still not viable in many potential applications due to their high cost, especially hyperspectral imaging instrument. Most of the experiments used for the analysis of meat quality and safety are just applicable in the laboratory because some of these technical tools are expensive, and others are extremely sensitive to environmental factors such as temperature and humidity. To satisfy the need for cost-effectiveness and sensitivity, developing a cheap and universal-specific instrument is especially important for the analysis of meat quality and safety. Data processing speed is still a bottle-neck in heavy-duty real-time applications, failing to handle the large data streams. Therefore, choosing an advanced and practical machine learning algorithm is a precondition for a successful application of these advanced analytical tools for analysis of meat quality and safety. Exploring adequately accurate and efficient data processing algorithms can accelerate processing speed to meet modern manufacturing requirements. With the availability of cheap and fast solutions software, data processing techniques will play a significant role in the rapid and intelligent inspection of meat quality and safety on a real-time basis. As online analytical techniques for monitoring of meat quality and safety become available, the need for monitoring of meat processing in order to guarantee meat quality homogeneity will become prime. For these techniques to facilitate the automation of meat applications and processes, the choice of suitable system parts in contact with the processed materials to enable the successful use of these tools for automated inspection, handling, and processing of meat will become relevant.

Finally, in spite of the great potential of the techniques discussed for real-time quality and safety monitoring of meat, their practical application may well be limited by the fact that they need a laborious calibration for prior their usage. That notwithstanding, developing high performance and low-cost on-line equipment for meat quality evaluation will be an observed trend in future application of these techniques in meat industries. Even though the present review focused on meat quality and safety, the principles are broader and generally applicable to other food ingredients and products.

Conclusions

Optical nondestructive techniques such as NIR spectroscopy, hyperspectral and multispectral imaging, and odor sensing techniques, specifically MOS and CSA, and their data fusion combined with appropriately selected multivariate algorithms have clearly shown great promise for possible future application to nondestructive detection of meat quality and safety. Based on the studies reported so far on meat quality and safety, these techniques have been applied successfully to predict qualitatively and quantitatively various key intrinsic quality and safety attributes pertinent to pork, chicken, and beef; which are the most widely produced and consumed meat sources globally.

However, there have been some general and individual challenges in some of these techniques such their affordability, non-portability and complication involved in their calibration and data analysis that affect their applicability to real-time meat quality and safety monitoring. That notwithstanding, the development of fast processing hardware, software applications, relevant chemometric algorithms, and the fabrication of simple but robust and portable systems, and their subsequent adoption in the meat industry will aid significantly to improve and guarantee the production of quality and safety meat. These techniques, by all indications, are likely to be the future trend of safeguarding the quality and safety of meat based on their real-time monitoring for the protection of consumers health and ensuring competitiveness among producers.

Conflict of interest

Authors wish to declare no conflict of interest.

Compliance with ethics requirement

This article contains no studies with human or animal used as subjects.

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