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Running title: Recent research in meat quality detection

A review on meat quality evaluation methods based on non-destructive computer vision and artificial intelligence technologies

Abstract: *Increasing meat demand in terms of both quality and quantity in conjunction with feeding a growing population has resulted in regulatory agencies imposing stringent guidelines on meat quality and safety. Objective and accurate rapid non-destructive detection methods and evaluation techniques based on artificial intelligence have become the research hotspot in recent years and have been widely applied in the meat industry. Therefore, this review surveyed the key technologies of non-destructive detection for meat quality, mainly including ultrasonic technology, machine (computer) vision technology, near-infrared spectroscopy technology, hyperspectral technology, Raman spectra technology, and electronic nose/tongue. The technical characteristics and evaluation methods were compared and analyzed; the practical applications of non-destructive detection technologies in meat quality assessment were explored; and the current challenges and future research directions were discussed. The literature presented in this review clearly demonstrate that previous research on non-destructive technologies are of great significance to ensure consumers' urgent demand for high-quality meat by promoting automatic, real-time inspection and quality control in meat production. In the near future, with ever-growing application requirements and research developments, it is a trend to integrate such systems to provide effective solutions for various grain quality evaluation applications.*

Keywords: *Meat quality; Non-destructive detection; Key technology; Grading assessment; Industrial application*

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1. Introduction

Meat is the main source of protein and has great physiological value for people. Meat (beef, poultry, pork, and lamb) consumption keeps increasing every year around the world (Smet and Vossen, 2016; Zhang et al., 2017). According to the Organization for Economic Co-operation and Development (OECD)'s 2017 report, the average meat consumption per person is expected to increase to 35.5 kg (78.3 lb) globally by 2024 (OECD, 2017). With meat consumption growing, quality is becoming more and more important to consumer's purchase decision (Wei et al., 2019). And research shows that meat quality is the most important purchase parameter affecting a consumer's decision (Kamruzzaman et al., 2016a; Barbon et al., 2017).

Meat quality assessments have two major measurement methods, subjective and objective (Li et al., 2018). Subjective methods for meat quality assessment usually depend on sensory evaluation, which involve visual and eating experiences. The disadvantage of subjective assessment methods is that they are highly dependent on particular experience of evaluators, poor repeatability, and can be difficult to quantify (Andersen et al., 2018; Cheng et al., 2017a). Objective evaluation methods have historically been laboratory tests evaluating the physical and chemical properties of and the microorganisms present in meat (Kamruzzaman et al., 2015). Which produces accurate results, but the meat product is damaged or destroyed, and the detection procedure is cumbersome. Inherently, objective evaluation method is time-consuming and high-cost, resulting in difficulty meeting the demand of automated processing for modern meat production companies (Chen et al., 2016). Countries around the world urgently need a fast, accurate, and non-destructive online detection technology for consistently evaluating meat to promote the healthy and stable development of food safety and quality (Qu et al., 2012).

Artificial intelligence (AI) technology is one of the most popular topics and is becoming an essential part of industries all over the world. Many industries in our lives have been permeated by AI technology, including auto-pilot vehicles (Yan, 2017), medical science (Salman et al., 2017), agricultural science (Gan et al., 2011), and food engineering (Barbri et al., 2014). Relevant to this review, AI technology has become important in the application of non-destructive prediction of meat quality, providing indispensable technical support for online meat grading and evaluation (Cheng et al., 2017b; Davies, 2009). In food science, AI technology that combines sensors, processors (computers), and other components allow for non-destructive evaluation of products, which result in the original shape, state, and nature of the sample being maintained (Wang et al., 2017). This technology uses the mechanics, optics, acoustics, electricity, and other pertinent information of the measured object to evaluate the physical characteristics, chemical composition, structural characteristics, and other data (Su et al., 2017), so as to achieve non-destructive and accurate evaluation of food quality.

In recent years, with the improvement of people's awareness of food safety and the advancement of computer technology, non-destructive evaluation technology has been applied more and more widely in the field of meat quality testing (Chen et al., 2013), including ultrasonic technology (Liu et al., 2016), machine vision technology (Sun et al., 2016), spectral technology (Muhammad et al., 2018), and sensor technology (Li et al., 2016). At present, scholars around the world have done a lot of in-depth research on the application of AI technology in meat quality testing, such as sensory quality evaluation (meat freshness, tenderness, color and texture) (Cheng et al., 2018). The prediction of physical and chemical indicators of meat quality (meat pH, shear force, water retention, moisture content, protein) (Pang et al., 2014; Sun et al., 2014) and the analysis of meat varieties, metamorphism mechanisms, and adulteration identification (Feng et al., 2018) have also been researched fairly extensively.

This review introduces the common AI technologies used for non-destructive evaluation of meat quality attributes in recent years including computer vision system (CVS), near-infrared (NIR)

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spectroscopy, hyperspectral imaging (HSI), Raman spectrometry (RS), ultrasonic imaging, and electronic nose/tongue technologies. The principle characteristics and application status of AI technologies in meat quality testing, grading, and evaluation are explained. In addition, current challenges and future development directions are also discussed in this review, so as to create a comprehensive knowledge base including essential theoretical basis and technical references for AI technologies used to improve human food quality and safety.

2. Non-destructive detection methods used with meat

With the increasing concern and attention of consumers, businesses and government departments, food quality and safety have been continuously studied in depth for long-term by domestic and foreign food scientists, and the non-destructive detection technology for meat quality has achieved a lot stage achievement (Chen et al., 2013). Commonly used non-destructive detection methods for meat quality are mainly focused on CVS, NIR, HSI, RS, ultrasonic monitoring, and electronic nose/tongue detection technologies.

2.1 Computer vision system

Computer vision technology, also known as machine vision technology that obtains target image information through image sensors instead of human eyes, and applies computer technology to analyze and process bionic human brains to convert image into digital information, and then to identify, track, and detect target objects (Girolami et al., 2013). A common machine vision detection system is shown in Figure 1 (Ma et al., 2016), which mainly includes a computer, an industry camera, an illumination system, and an image processing software system (Taheri-Garavand et al., 2019b).

Figure 1 A common machine vision detection system

Due to the rapid advancement in computer technologies, the development of image processing technology and the machine vision based non-destructive detection systems have been widely used in extracting image-based features and feature recognition related to detecting meat quality. Sun et al. (2016; 2018) developed a CVS for objective measurement of pork loin quality. Color features (L*, a*, and b*) and marble patterns in the region of interest in an image of a meat cut were extracted. Subsequently, an artificial intelligence prediction model (support vector machine (SVM)) was developed for determining pork color and marbling quality grades with a highest prediction accuracy of 92.5% and 75.0%, respectively. Liu et al. (2018b) investigated the ability of CVS to predict pork intramuscular fat percentage (IMF%) coupled with the development of stepwise regression and SVM models. Arsalane et al. (2018) applied an embedded machine vision system based on digital signal processing (DSP) to evaluate beef freshness. Results showed perfect prediction (classification and identification 100%) accuracies with new unknown samples using both principal component analysis (PCA) and SVM.

In addition, some studies have been attempted for the application of CVS to monitor meat defects. Chmiel et al. (2012) evaluated the potential of CVS to detect DFD (dark, firm, and dry) beef. A significant relationship was found among L*, a*, and b* color components with pH, which

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is an indicator to detect DFD beef. Chmiel and Słowiński (2016b) determined the effectiveness of a CVS in measuring meat color to detect meat defects of *m. longissimus lumborum (LL)* in industrial settings. They reported that the CVS showed a strong promise to detect PSE (pale, soft, exudative) and DFD and to classify meat into quality groups.

Table 1 lists the typical applications of machine vision technologies as non-destructive detection methods for meat quality attributes during the recent years. These literatures have revealed that the current applications of CVS in meat quality inspection have been using the external features such as color or texture-based features extracted from the images acquired in visible region of the spectrum and combed with the stoichiometric methods for qualitative or quantitative analysis. However, the CVS method was found unable to express the characteristics of the internal components of the meat samples. The CVS is mainly used to detect external properties such as meat color, marbling pattern, tenderness, freshness, and fat content in one hand. On the other hand, CVS is unable to measure the internal characters such as moisture content, and protein content (Taheri-Garavand et al., 2019b; Brosnan and Sun, 2004).

Table 1 Typical applications of machine vision technologies

2.2. Near-infrared spectroscopy technique

Near-infrared spectroscopy (NIR) is an electromagnetic radiation wave with a wavelength range of 780-2526 nm between visible and mid-infrared light and referred as the first non-visible spectral region found in the absorption spectrum (Wang et al., 2015). And the spectral curves displayed by different chemicals in the near-infrared region are different (Cai et al., 2011; Wang, 2012b). Therefore, the correlation between the original spectral data of the samples in the full wavelength range and the corresponding physical and chemical index values (function relationship) can be used to analyze (identify and quantify) the chemicals and their constituents (ElMasry et al., 2011; Alexandrakis et al., 2012). As a result, it can be perceived that based on the basic principles of NIR spectroscopy and the NIR detection system as shown in Figure 2 (Xiong et al., 2015b), the degree of putrefaction in meat storage and the physical-chemical properties and parameters (such as moisture, protein, fat, water retention, gravy loss, etc.) during processing can be detected (Collell et al., 2011).

Figure 2 Basic principles of NIR spectroscopy and the NIR detection system

Deterioration, spoilage, and decreased freshness of meat are closely related to moisture, protein, and fat content. The NIR spectroscopy can objectively reflect these changes of organic components such as fat and protein in fresh meat (Jiang et al., 2017a). Liu et al. (2009) detected fat, protein, and water by visible and NIR (Vis-NIR) transmittance spectroscopy in chilled pork. They found that the performance of evaluation model was hopeful, and the correlation coefficients were 0.95 and 0.92 for fat, 0.71 and 0.46 for protein, and 0.94 and 0.91 for water respectively. Liao et al. (2010) used Vis/NIR spectroscopy to predict quality attributes of fresh pork (content of intramuscular fat, protein and water, pH, and shear force values) on-line. Results showed that the prediction models yielded

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high coefficient of determination (R^2) of 0.757 or more for all traits except for the prediction of shear force values. Guy et al. (2011) assessed the feasibility of NIR spectroscopy for predicting lamb meat fatty acid composition and demonstrated the accuracy of the prediction models through analyzing and comparing the measured reflectance spectrum of *Longissimus lumborum* muscle. Tian et al. (2013a) studied the on-line detection and classification models of multi-quality parameters for fresh beef based on Vis/NIR reflectance spectroscopy. The prediction model showed a better performance with the correlation coefficient of 0.91 for beef tenderness, 0.89 for $L*$, 0.93 for $a*$, 0.85 for cooking loss with a highest classification accuracy of 93.5% for beef tenderness.

In recent years, scholars worldwide have conducted many studies on the freshness detection of fresh meat using Vis/NIR spectroscopy technique particularly to predict total volatile basic nitrogen (TVB-N) and microbes as indicators. Wang et al. (2015) applied Vis/NIR spectroscopy to quantitatively evaluate pork TVB-N. The correlation coefficient was 0.98, which demonstrated the huge potential for Vis/NIR spectroscopy application to analyze pork freshness. Cai et al. (2009) applied NIR (1100-2500 nm) spectroscopy to detect the TVB-N content in pork and used synergy interval partial least squares (siPLS) algorithm for building the calibration model of TVB-N content. Guo et al. (2014) used near-infrared hyperspectral imaging (NIR-HSI: 900-1700 nm) technology to detect the TVC on chilled mutton surface to indicate the degree of contamination and degradation of meat. The corresponding correlation coefficient and the root mean square error of prediction (RMSEP) were 0.99 and 0.25, respectively.

Table 2 shows the extensive application of NIR spectroscopy in the field of rapid non-destructive detection for meat quality in the past years. It can be seen that the current research on the detection of meat nutrient components based on NIR spectroscopy is relatively mature. Typically, the spectral data is a reflection of the internal chemical constituents in meat specimens, which is mostly used for meat identification, recognition and classification, while ignoring the influence of external attribute characteristics on meat quality changes (Zhu et al., 2019). The prediction accuracy of NIR technique for predicting sensory quality of meat is not high enough, which is in sharp contrast with machine vision technology (Dixit et al., 2017).

Table 2 Application of NIR spectroscopy in the field

In addition, a single indicator can only describe one aspect of the characteristics of meat quality changes, which is another limitation of this method (Wiedemair et al., 2018). Therefore, it is necessary to find an innovative and advanced technology that can simultaneously possess the technical feature of NIR spectroscopy and CVS technology, taking into account the characteristics of internal components and external attributes of meat samples (He et al., 2019), so that make the meat quality detection become more comprehensive, accurate, stable, and sustainable.

2.3. Hyperspectral imaging technique

Hyperspectral imaging (HSI) technology is a derivative spectral detection technique based on hyperspectral remote sensing imaging technology. The spectral band of HSI covers all continuous bands in ultraviolet, visible, near-infrared, mid-infrared, far-infrared, and thermal infrared regions.

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HSI technology is an emerging and rapidly developing photoelectric detection fusion technology (Li et al., 2018; Xiong et al., 2015b) that combined the spectral detection technology with digital computer vision technology (two-dimensional imaging technology) and facilitated the integration of the spectral resolution and image resolution. Spectral information reflects the internal properties (mainly constituents) of the samples, and image information reflects the external features. When acquiring sample composition index retains its original physical and chemical properties, achieving rapid, accurate, and non-destructive detection of the samples (He and Sun, 2015; Liu et al., 2018a). HSI techniques can be divided into visible/near-infrared hyperspectral imaging techniques (Vis-NIR-HSI: 400-1000 nm) and near-infrared hyperspectral imaging techniques (NIR-HSI: 900-1700 nm) according to the covered wavelength range of the electromagnetic spectrum. Compared to NIR, hyperspectral imaging techniques integrates near-infrared spectroscopy and high-resolution imaging technology, which can acquire both spectral and image information in real time and simultaneously.

Figure 3 Hyperspectral image is a three-dimensional data cube

The technical principle of hyperspectral imaging is to use the traditional integrated hardware and software platform of two-dimensional imaging and spectroscopy to obtain both spatial and spectral information of each pixel of the object. Then, conduct qualitative and quantitative analysis on the obtained data through stoichiometry, so as to reflect the comprehensive properties and characteristics of the object to be measured (Cheng et al., 2015; Liu et al., 2017). HSI is a three-dimensional data cube in which spectral images composed of spectral data in hundreds of consecutive bands are arranged in a spectral order, called a hypercube or a spectral cube (x, y, λ), as shown in Figure 3, where (x, y) is x, y coordinate value of the pixel in two-dimensional image, and the third dimension is the wavelength λ coordinate value, which representing the one-dimensional spectral dimension. Seeing from the one-dimensional dimension (λ), the HSI is a two-dimensional (x, y) image (Fig. 3a), and from the two-dimensional (x, y), the HSI is a strip of spectral lines (Fig. 3b) (Cheng et al., 2017a; Piqueras et al., 2012). Therefore, the two-dimensional image information of a certain wavelength point of the sample from the hyperspectral data cube can be extracted, and the absorbance value of a certain point or a certain region of the sample at each wavelength point can also be extracted, that is the spectral information at each point of the samples (Elmasry et al., 2012; Abasia et al., 2018).

Generally, HSI technique combines the advantages of spectral analysis and image processing technology, and can rapidly and non-destructively extract the chemical composition, physical properties, and other related indicators of samples. Liu et al. (2014) investigated the utility of HSI techniques (400-1000 nm) for predicting the color and pH of salted porcine meat. The model predicted L*, a*, and pH values with coefficients of determination of 0.72, 0.73, and 0.86, respectively, using small. Kamruzzaman et al. (2011; 2012) explored the potential of NIR-HSI in combination with multivariate analysis for the prediction of some quality attributes of lamb meat. The PLSR models performed well for predicting pH, color, and drip loss with the R^2 of 0.65, 0.91

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and 0.77, respectively. Furthermore, HSI technique is widely used in the field of food quality and safety, non-destructive testing, and has great potential for development of applications in the detection and classification of meat quality. Barbin et al. (2013) developed a push-broom NIR_HSI (900-1700 nm) to determine the TVC and psychrotrophic plate count (PPC) in chilled pork during storage, and best regressions were obtained with R^2 of 0.86 and 0.89 for TVC and PPC, respectively. Kamruzzaman et al. (2016b) investigated a hyperspectral real-time imaging system in the spectral range of 400-1000 nm to monitor the changes of moisture content in red meat (beef, lamb, and pork). Xiong et al. (2015a) evaluated the potential HSI technology to predict hydroxyproline content in chicken meat. Their models yielded acceptable results with R^2 0.87 in the prediction phase.

Table 3 lists the typical applications and achievements of HSI technology as non-destructive detection methods for meat quality determination in recent years. It was observed that the research based on HSI technology as the non-destructive detection methods for meat quality determination mainly includes: evaluation of safety indicators such as surface contamination and TVC; evaluation of sensory quality such as freshness, color and pH; detection of nutrient content such as meat moisture, protein and fat; as well as the real-time monitoring of processing train and classification of meat quality. Overall, HSI technology is recognized to be one of the fastest growing and most widely used techniques for non-destructive testing of meat quality and safety in recent years.

Table 3 Lists the typical applications and achievements of HSI technology

2.4. Raman spectra technique

Raman spectroscopy is a spectral analysis technique developed based on Raman scattering effect. It is generated by the change of polarizability, caused by the vibration of sample molecules, and can provide the vibration or rotation information of molecules (Li et al., 2019). Each functional group molecule in the meat has its own unique Raman spectral signal, which is mutually complementary with the infrared spectrum in the analysis of the molecular structure (Chen et al., 2012; Liu et al., 2015b). Therefore, representative information in the Raman spectrum of meat can be extracted with the method of chemometrics, the relationship between the molecular structure and various radical groups in meat can be qualitatively analyzed, and then meat quality can be detected and evaluated.

In recent years, Raman spectroscopy has been increasingly applied in meat quality. Fowler et al. (2014) used a handheld Raman probe to predict the shear force (SF) of fresh lamb, the correlation between tenderness and Raman data was established based on PLSR method, and the SF prediction model was found to have good accuracy. Bauer et al. (2016) applied a portable 671 nm Raman monitoring system to assess beef tenderness. SF measurements were performed and the results showed that tough and tender samples could be discriminated with 70-88% and 59-80% accuracy, respectively. Wang et al. (2012c) developed a Raman spectroscopic method to evaluate and predict the sensory attributes (tenderness, juiciness, and chewiness) of fresh, uncooked pork loins. The SVM method were able to differentiate and classify the pork loins into quality grades ("good" and "bad" in terms of tenderness and chewiness) with a prediction accuracy of > 83 % in comparison to

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sensory panel results.

In addition, semi-quantitative analysis can be performed according to the proportional relationship between the peak intensity of Raman spectrum and the concentration of measured substance. Han et al. (2014b) investigated the effect of NaCl concentration on the functional characteristics of pork myofibrillar protein (PMP) heat-induced gelation by textural analysis and Raman spectroscopy. Results indicated obvious changes of hardness and Raman spectroscopy of the PMP gel occurred with the increasing NaCl level. Xu et al. (2011) also appraised the use of Raman spectroscopy to study structural changes, textural properties and their relationships in PMP, combined with texture profile analysis (TPA) and PCA. With scholars' deepening research on Raman spectroscopy, the application of Raman spectroscopy in meat processing and production is also gradually increasing. Zhang et al. (2015b) applied Raman spectroscopy to investigate the effects of high-pressure (100-500 MPa) on chemical forces and water holding capacity (WHC) of heat-induced myofibrillar protein (MP) gel. Pedersen et al. (2003) revealed a high correlation between the WHC of meat and the Raman spectrum using PLSR. They found that region 1800-1900cm^{-1} contains the best predictive information that responded to WHC of the porcine meat. Scheier et al. (2014) performed a mobile Raman system to measure and predict important meat quality traits under real-life conditions of an abattoir using pig's *semimembranosus* muscles. The traits of pH values, CIE L*a*b*, drip loss, and SF after 24 and 72 h were measured as reference and correlated with the Raman spectra using PLSR. Fowler et al. (2015a) conducted the complementary studies to evaluate the potential for a Raman spectroscopic device to predict the quality traits of fresh lamb *m. semimembranosus* after ageing and freezing/thawing.

Also, the chemical structure of functional group molecules can be detected using Raman spectroscopy, and thus identifies meat quality. Boyaci et al. (2014) applied Raman spectroscopy and chemometric method (PCA) to rapidly differentiate the origin of the meat based on their extracted fat samples. Collected Raman data were analyzed with a four-stage PCA method, and seven meat species (cattle, sheep, pig, fish, poultry, goat, and buffalo) were successfully differentiated from each other according to their origin. Zając et al. (2014) proposed a new method based on FT-Raman measurements to determine the content of horse meat in its mixture with beef. The reasonable results showed good fitting between the spectroscopic parameters and chemical content of the studied samples, and analytical equations between these parameters have been proposed.

Recently, the application of Raman spectroscopy in the field of meat detection is more and more extensive and comprehensive. Table 4 lists the research on the detection of meat quality using Raman spectroscopy in the past 5 years. It can be seen that exploring quality change law in meat processing and evaluating meat safety mechanism are still the focus and direction of Raman spectroscopy in meat science research and industrial production applications.

Table 4 Lists the research on the detection of meat quality

2.5. Ultrasonic imaging technique

Ultrasonic can be divided into two types in practical applications, namely power ultrasonic

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waves and detection ultrasonic waves. The ultrasonic generated by power ultrasonic is of low-frequency and high-energy, which is usually used in food processing, such as food sterilization, thawing, drying, filtration, and homogenization. The ultrasonic produced by detection ultrasonic is of high-frequency and low-energy and commonly used to analyze and detect food quality (Wang et al., 2019). Ultrasonic techniques for detecting meat quality is based on the analysis of changes in acoustic characteristic parameters for predicting meat composition, muscle thickness, fat thickness, etc. Rapid and non-destructive detection and grading evaluation for meat quality are achieved without changing the internal traits of meat (Soria and Villamiel, 2010; Zhang et al., 2018).

Benedito et al. (2001) evaluated the changes in ultrasonic velocity to detect the composition of meat mixture. Fat, moisture, and protein can be determined by measuring the ultrasonic velocity in the mixtures using a semi-empirical equation. Li (2013) used ultrasonic imaging technique to identify the fat content of pork loin by analyzing B-mode ultrasound images. The SVM classifier combined with BPANN algorithm was designed to detect and classify the fat content with a classification accuracy of 94.9%. Fukuda et al. (2013) developed an image recognition method using a neural network to accurately estimate the beef marbling standard (BMS) number of live cattle using ultrasound echo imaging, and the results confirmed that the correlation coefficient between the actual and the estimated values was 0.70 ($p < 0.01$). Prados et al. (2015) researched the feasibility of using low-intensity ultrasound (US) technology to predict the salt content in brined *Biceps femoris* (BF) and *Longissimus dorsi* (LD) pork muscles. Results obtained significant linear relationships between the US velocity and both factors ($R^2 > 0.77$). Ayuso et al. (2013) assessed the use of ultrasound measurements in live animals to predict carcass composition, ham, foreleg weights, and lean meat yields of Iberian pigs. All the results showed high correlation coefficient ($R^2 = 0.84$) between measured and predicted attributes.

The research on ultrasonic detection technology applied in the field of non-destructive testing for meat quality started earlier. It was mainly used to detect the content of moisture, fat, protein, and other components of meat as well as online detection and classification for pork carcasses. There have been some ultrasonic carcass grading systems for commercial applications abroad such as the UltraFom 300 and AutoFom in Denmark and CVT-2 in the United States (Fortin et al., 2004). However, ultrasonic detection is susceptible to the irregularities of the tested meat, the uneven distribution of fat and lean meat, the measurement site, the ultrasonic frequency, etc., will cause large measurement errors (Jiang et al., 2017b). In recent years, ultrasonic technology has been mainly applied in food processing, which is reflected in the sterilization, pickling, tenderization, thawing, freezing, etc. of meat, as well as the use of ultrasonic assisted extraction of components in food, improvement of meat quality, etc. (Fu et al., 2017; Ojha et al., 2017; Pérez et al., 2018; Suo et al., 2018; Zhang et al., 2019; Zou et al., 2018).

2.6. Electronic nose/tongue sensor technique

Odor has always been an important indicator to judge the meat grade when consumers perceive

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the meat quality with their senses. During meat storage, with the decrease of freshness, the proteins, fats, and carbohydrates will be decomposed successively under the action of enzymes and bacteria, and thus, the smell of spoiled meat will become more and more intense (Kizil et al., 2015). Coincidentally, electronic nose is a kind of gas-sensitive sensor that is sensitive to various chemical substances and simulates the olfactory function of human nose, also known as artificial olfaction. It is an intelligent system that can sense and identify volatile gases, used to conduct odor detection and deterioration degree evaluation (Jia et al., 2018).

Many scholars at home and abroad have used the electronic nose technology to detect the change of meat odor, so as to judge the freshness of meat, and predict the shelf life of storage. Xiao and Xie (2010) and Li et al. (2016) both used electronic nose (E-nose) technology to detect changes in volatile components of chilled pork at different storage temperatures and periods, so as to assess the freshness of chilled pork. PCA method and discriminate factorial analysis (DFA) was used to analyze the E-nose signals by combining the changes of physical chemistry index such as TVC and TVB-N. Wang et al. (2012a) used an E-nose together with SVM to predict the TVC in chilled pork. The correlation between E-nose signal responses and bacterial numbers was established using the SVM combined with PLS. Jia et al. (2011) discussed the feasibility of meat adulteration recognition based on E-nose that used to analyze yak meat, beef, and pork, and the results indicated that E-nose could recognize yak meat, beef, and pork, and could recognize yak meat and beef samples at different growing locations.

At the same time, as the meat is spoiled, this condition changes the conductivity, and electronic tongue (E-tongue) which is an electronic circuit used to measure this conductivity (Wang et al., 2016). The E-tongue is an intelligent detection system composed of a taste sensor array and a pattern recognition system that can imitate the function of human taste system. In the application of meat quality detection, E-tongue sensor acquires the signal of the taste substance, and the computer uses the pattern recognition algorithm to analyze and identify the meat composition and metamorphic degree, as well as distinguish different meats (Tian et al., 2013b). Wang et al. (2012d) used the multi-frequency pulse E-tongue system to discriminate chicken meat quality. Results suggested that significantly different E-tongue sensor signals were observed for raw breast and leg samples from the same chicken breed. Similarly, Gil et al. (2011) also used E-tongues to describe the correlation found between potentiometric measurements and the variation in certain physicochemical, microbial, and biochemical parameters measured on a whole piece of pork loin stored in a refrigerator. Ultimately, they found a remarkable correlation between pH, so-called K-index, and the potentiometric data.

Generally, it was observed that the E-nose/E-tongue sensing technology mainly achieves the evaluation of meat freshness, the identification of meat varieties and quality, and the judgement of spoilage level and storage time based on the smell or taste. The test requirement of collection environment is relatively high, and the detection index is relatively simple and single, which cannot satisfy the requirement of multi-index comprehensive evaluation for meat quality (Han et al., 2014a).

2.7. Other meat quality detection techniques

With the rapid development of artificial intelligence in the field of meat quality detection and in addition to the above-mentioned commonly used non-destructive testing technology, following non-destructive detection techniques for meat quality have emerged:

Nuclear magnetic resonance spectroscopy (NMR) is based on the principle of energy exchange between a magnetic nucleus and a radio frequency magnetic field to detect the structure of various organic or inorganic compounds. The technology has been widely used in medicine and achieved great success (Damez and Clerjon, 2013), afterwards, some scholars have applied it to the detection of internal ingredients in food. Shaarani et al. (2006) demonstrated the usage of a combination of bulk NMR and magnetic resonance imaging (MRI) measurements of the T2-values of water protons to determine the heat-induced changes in the structure and moisture content of fresh chicken meat. Graham et al. (2010) combined the data generated by NMR spectroscopy with chemometrics to determine the changes in polar metabolite concentrations in beef *longissimus dorsi* stored for different periods postmortem. Findings demonstrated the potential of this novel approach of using high resolution NMR spectrometry to be used as a suitable method for profiling meat samples. Liu et al. (2013) investigated the influence of age on the chemical composition of duck meat using the ^{1}H NMR spectroscopy. Their results contribute to be used to help assess the quality of duck meat as a food. Xiao et al. (2019) characterized the effect of the process (washing, boiling 1 h with salt, deep frying, and boiling 2 h) on the water-soluble low molecular weight (WLOM) compound profiles of products using proton NMR spectroscopy, and the fatty acid composition of products was analyzed using gas chromatography-mass spectrometry. However, in terms of food science, NMR is mainly used for the analysis and detection of water, protein, fat, carbohydrate, and some trace elements, through analyzing the changes of chemical substances in meat to explore the change mechanism and causes of flavor, color, and tenderness (Yang et al., 2012).

Bioimpedance is a basic physical parameter of biological tissue, mainly reflects the complex dielectric properties of biological tissues, organs, cells or whole biological organisms. The measuring principle of this technique is to input tiny alternating current (or voltage) on the surface of the test object through electrodes, then obtaining the physiological or pathological information based on the changes in dielectric properties in terms of potential difference (Peng et al., 2011). Fang et al. (2008) investigated the variations and mutual relationships between bio-impedance values, pH value, and water loss rate of bovine muscles near freezing point. The results revealed that the correlation between bio-impedance and pH, and water loss rate are significant ($P \geqslant 0.05$). Yang et al. (2013) used bioelectrical impedance spectroscopy to measure moisture content in porcine meat, and forty-four pieces of porcine *longissimus dorsi* muscle (LDM) were evaluated with a four-terminal electrode in a portable bioimpedance spectroscopy system. Xie et al. (2016) established a method for rapidly detecting the freshness of chilled pork based on bioimpedance technology. The

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TVB-N content, impedance, and phase angle of 20 samples were measured and evaluated for their bioimpedance characteristics. Li et al. (2014) studied electric impedance magnitude and phase properties of unfrozen and frozen-thawed chicken breasts subjected to different thawing times to explore the impedance detection ability for frozen–thawed meat. Radial basis function (RBF) neural network was used to extract the impedance and amplitude information. It is observed that, in recent years, bioimpedance analysis has been widely used to predict the pH value, fat content, water activity, etc., as well as to determine the freshness and maturity of meat.

X-rays have the characteristics of penetrating power, diffractive action, and excitation fluorescence. This is done by capturing the difference of attenuation degree occurring after the interacting with atoms of different substances. When X-ray penetrating, the transmission images and tomographic images of samples can be obtained for further analysis of internal structure (Karoui and Blecker, 2011), so as to enable virtual segmentation of the carcass for grading. Nassy (2015) studied X-ray tomography to measure and evaluate porcine carcass composition and quality traits. The proportion of three main tissues, fat, lean, and bones were determined by X-ray computed tomography (CT), and then the carcass was well graded according to the thickness of the fat and lean. Tao and Ibarra (2000) proposed a new method to compensate for x-ray absorption variations to detect the bone fragments in poultry meat with uneven thickness. Experimental results demonstrated that the proposed imaging method eliminated the false patterns and enhanced the sensitivity of X-ray in bone fragment detection. Chen et al. (2017) analyzed the physical characteristics of Sanhuang chicken carcass based on CT image technique (X-ray scanning technique), and the experiment results showed that the relative position of the heart, lung, muscle, stomach, and kidney could be clearly determined based on the horizontal and vertical cross-sectional CT images of the carcass. Liu et al. (2015a) studied the value of application in predicting the intramuscular fat (IMF) content and other nutrition in sheep carcass with dual-energy X-rays, and the results proved the necessary basis for the application of dual-energy X-ray in the prediction and evaluation of meat quality. In addition, Furnols et al. (2009) used CT technique coupled with PLS regression to estimate the lean meat percentage (LMP) in pig carcass, indicated that for CT scanning data achieved a good prediction of the LMP of the whole carcass.

3. Applications

In recent years, with the increasing attention and continuous development of artificial intelligence, additionally, the growing demand for high-quality and safe meat paired with increasing population, various non-destructive detection technologies have become more and more widely used in the field of meat quality testing (Chen et al., 2013). Throughout the existing research achievements on non-destructive detection for meat quality (Table 1-Table 4), the studies on meat quality mainly focuses on the four categories of beef (Wei et al., 2019), pork (Sun et al., 2018), lamb (Zheng et al., 2019), and poultry (chicken) (Jiang et al., 2017a), including the evaluation of sensory

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characteristics, detection of nutrient components, identification of physical-chemical properties, discrimination of processing quality (quantitative analysis) and judgement of safety quality (qualitative analysis) (Taheri-Garavand et al., 2019b).

Sensory quality directly affects consumer's desire to purchase, which reflects the commodity value of meat. It is generally evaluated from the aspects of meat color, marbling, freshness, tenderness, flavor, and juiciness. Among them, the meat flavor is closely related to the nutrients such as amino and fatty acids, and the juiciness is closely related to the fat and moisture content in meat. Sun et al. (2016) utilized a CVS to predict pork color attributes. A CVS developed for meat marbling classification resulted in accuracy values of 81.59 % for bovine and 76.14 % for swine. Wei et al. (2019) proposed a method for detecting beef freshness based on multi-spectral diffuse reflectance technique coupled with a LS-SVM for establishing a freshness prediction model, which yielded a correlation coefficient greater than 0.85. Bauer et al. (2016) evaluated a portable 671 nm Raman system to assess the tenderness of aged bovine *gluteus medius* muscles, and established a prediction model for beef tenderness by PLSR method that obtained 88% accuracy. Zhang et al. (2019) studied the effect of ultrasound technology on the tenderness of goose breast meat. Zhao et al. (2018) developed a rapid analytical technique to predict beef flavor using RS and to investigate correlations between sensory attributes of young dairy bull beef using chemometric method.

Nutritional components reflect the edible value of meat, which mainly refers to the monitoring and analysis of meat moisture, protein, fat, vitamins, and minerals. Peng et al. (2018) designed and developed an on-line detection and grading system for pork moisture based on NIR spectroscopy modeled with the PLSR technique for predicting and grading of pork moisture. Liu et al. (2009) determined the fat, protein, and water in chilled pork using Vis-NIR transmittance spectroscopy coupled with PLS model. This result showed that the Vis-NIR method could measure the fat and water contents in chilled pork well, however, not found suitable for protein. Liu et al. (2018b) investigated the ability of CVS to predict pork intramuscular fat percentage (IMF %). The accuracy rates for regression models were 0.63 for stepwise and 0.75 for SVM. For better predicting intramuscular fat contents in pork muscles using hyperspectral imaging, Ma et al. (2018) employed a novel correlation-optimized warping (COW) technique with the first derivative on the full spectra and the feature wavelengths selected by successive projections algorithm.

Physical-chemical properties are the inherent characteristics of meat. Therefore, the non-destructive detection technology is primarily applied for the prediction and evaluation of the microbial, pH, TVC, and TVB-N content of meat (He and Sun, 2015). Barbin et al. (2013) exploited another push-broom NIR-HSI (900-1700 nm) to study the undesirable microbial growths (TVC and PPC) caused by temperature fluctuation during chilled pork storage. Results were encouraging and showed the promise of hyperspectral technology for detecting bacterial spoilage in pork. Nache et al. (2016) presented a new approach to predict the pH values as quality indicator to assess porcine meat quality by combining Raman spectroscopy with the ACO metaheuristics. Yang et al. (2017a) investigated the feasibility of an HSI technique to determine the (TVC) of cooked beef during

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storage for evaluating the freshness state. The developed LS-SVM classification models yielded a high overall classification accuracy of 97.14%. Li et al. (2016) used E-nose to predict the TVC and TVB-N in pork and assessed the freshness of chilled pork during refrigerated storage under different packaging methods. Cheng et al. (2016) measured the biogenic amine index (BAI) in pork based on HSI data combined with stoichiometric analysis to evaluate meat freshness and quality. The PLSR technique showed an excellent prediction with a R^2 of 0.96.

Processing quality is an important reference for evaluating the meat processability. The commonly used indicator for characterizing meat processing is hydraulic power, also referred as drip loss or water retention, which is used to evaluate the ability of meat muscle tissue to retain water. ElMasry et al. (2011) carried out the post-mortem non-destructive prediction of WHC in fresh beef using NIR-HSI. The modeling of spectral data of beef samples to its real WHC estimated by drip loss method resulted in a R^2 of 0.89. An image processing algorithm was then developed to transfer the predicting model to each pixel in the image for visualizing drip loss in all portions of the meat sample. Barbin et al. (2015) tested the NIR reflectance as a potential technique for predicting the WHC of chicken breast (Pectoralis major). Spectra in the wavelengths between 400 and 2500 nm were analyzed using the PCA method and quality attributes were predicted using the PLSR. Results showed that the WHC was the most challenging attribute to determine with R^2 of 0.70 and SECV of 2.40%.

Safety quality is an important content of meat safety testing including the identification of meat varieties and origin, the recognition of components adulteration, and the qualification of corruption degree or shelf life. Chmiel and Słowiński (2016b) determined the effectiveness of a CVS to detect meat defects of *m. longissimus lumborum* (LL) in industrial settings. It was found that it is possible to employ the CVS to detect PSE (pale, soft, exudative) and DFD (dark, firm, dry) and to classify meat into quality groups. Geronimo et al. (2019) studied to identify and classify chicken with wooden breast (WB) using a CVS and spectral information from the NIR region by linear and nonlinear algorithms. A 91.8% of chicken breasts were correctly classified as WB or Normal (N), and NIR spectral information showed an accuracy of 97.5%. Ropodi et al. (2017) investigated the potential of multispectral imaging coupled with data analysis methods for the detection of minced beef adulteration with horsemeat, as well as to explore model performance during storage in refrigerated conditions, and the results showed that all pure and freshly-ground samples were classified correctly. Zheng et al. (2019) described a rapid and non-destructive method based on Vis-NIR-HSI system (400-1000 nm) for detecting adulteration with duck meat in minced lamb. The results indicated that the PLSR model with selected wavelengths achieved better results than others with a R^2 0.98. Xiao and Xie (2010) used E-nose technology to determine the freshness and shelf life of chilled pork. Studies had shown that the shelf life of chilled pork stored at temperatures of 283K and 277K was 2 d and 5 d, respectively.

4 Challenges and trends

It can be seen that with the popularization and development of artificial intelligence technology, through the unremitting efforts and pursuit of food scientists at home and abroad, non-destructive testing technology has achieved relatively desired research achievements in meat quality testing. However, most of the testing techniques adopt a single detection method for some specific detection index with acceptable predicting results, which cannot obtain multiple information to comprehensively evaluate the samples (Xiong et al., 2017).

Yet, meat quality is affected by many external factors, its contamination and deterioration are complex change process, which are the result of joint action between its internal components and external attributes. A single limited indicator can only describe one of the characteristics of quality changes limiting to achieve a comprehensive evaluation of meat quality as a whole, and the test results ultimately lack comprehensiveness, applicability and accuracy. Therefore, it is necessary to synthesize multiple detection methods and indicators, and utilize fusion of data information to study the comprehensive evaluation method for meat quality (Rosa et al., 2017). Geronimo et al. (2019) combined both CVS and NIR spectroscopy to identify and classify chicken freshness, respectively, and performed physical and technical characterization. Huang et al. (2014) attempted to use multi-source information fusion technology to further improve the accuracy of non-destructive testing, and effectively integrated NIRS, CVS, and E-nose techniques to evaluate pork freshness. Compared with single technique, integrating three techniques has its own superiority in improving the accuracy and stability of the freshness prediction performance significantly. Lu et al. (2011) have studied the complementary technologies of mid-infrared and Raman spectroscopy to rapidly differentiate and quantify the bacteria and microorganisms in meat with determinations taking less than an hour. Pérez-Palacios et al. (2014) combined magnetic resonance imaging (MRI) and CVS to forecast quality traits of Iberian hams by using non-destructive analysis and data mining methods.

The fusion of multi-source information will certainly bring great difficulties and challenges to data processing and analysis. Additionally, a large number of redundant images and added data information will call for higher requirements on the hardware performance of detection system. Therefore, it warrants the necessity to extract the useful information for inspection indicators as few and accurate as possible. Moreover, non-destructive testing is mostly indirect measurement that uses the stoichiometric method to establish relationship models between detection data and quality indicators through a certain number of test samples. The accuracy and reliability of the prediction models depend on effective modeling methods and original samples. Therefore, on the basis of ensuring the hardware performance (such as computing performance, camera resolution, and sharpness, etc.) of the detection system, it is urgent to optimize the statistical analysis methods to reduce unnecessary and irrelevant data information (Chen et al., 2013). Therefore, to speed up the system operation process, it is critical to establish more reasonable and improved regression algorithm models (PLSR, SVM, ANN, etc.) and machine learning for further mining data information to facilitate improvement of the prediction accuracy, efficiency, and overall performance (adaptability and robustness) of the meat quality detection system.

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Furthermore, most of the current non-destructive testing methods for meat quality remain at the experimental research stage, although it has been proved that the detection system can meet certain testing speed and precision. However, working performance of non-destructive technologies and their effects have not been verified in the real-world meat processing production line. Therefore, while strengthening the research intensity on detection methods, prediction models, and system equipment, it is critically necessary to validate the performance of the testing equipment in the actual production process and thus, to promote the demonstration application of detection system for meat quality and intelligent development of meat processing industry. An appropriate automatic commercial inspection system for meat quality testing can only be realized when a feedback on the performance of non-destructive technologies in industrial settings (real-time meat processing production line) are available.

5 Conclusions

In the event of continuously increasing people's demand for high-quality meat coupled with development of artificial intelligence including non-destructive testing technologies have been more and more widely applied in meat quality detection. Machine vision, near-infrared spectroscopy, hyperspectral, Raman spectroscopy, electronic nose/tongue, and ultrasonic imaging technologies have shown their respective unique technical characteristics when exposed to meat. Overtime, these technologies have achieved gratifying research achievements for the detection, evaluation and grading of sensory quality, nutritional quality, physical-chemical quality, processing and safe quality on the meat (beef, pork, lamb, poultry, and aquatic).

Nonetheless, machine vision technology is useful to obtain the appearance characteristics of meat such as color, surface morphology, etc., but, it is difficult to acquire the internal quality of meat using CVS. In contrast, NIR can detect the changes in internal composition of meat, but incapable of recognizing the external information such as meat color and odor. Unlike CVS and NIR, E-nose technology is mainly used to monitor the volatile gases released from meat and cannot determine the appearance color and internal composition changes of meat. The HSI technology integrates the advantages of both CVS and NIR methods, which facilitates predicting both internal characteristic information of the samples along with detecting the external basic spatial information. However, most of the studies only make use of the single spectral information or image information in hyperspectral data for modeling purpose. The characteristics of ‘combination of spectrum and image’ of the hyperspectral imaging technology are not fully utilized yet in conducting quantitative analysis and qualitative discrimination on comprehensive determination of meat quality parameters.

Therefore, multiple non-destructive testing technologies are organically integrated fully to obtain the multivariate data information of integrated sample that combined with the optimized and improved chemometric methods. Additionally, the digital image processing technology paired with artificial intelligence learning algorithms were used to construct quantitative prediction models and qualitative discrimination methods for meat quality. Furthermore, performing the comprehensive

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and entire evaluation of fresh meat from sensory characteristics, internal constituents and external factors, and applying the developed high-performance quality detection systems to actual meat processing production lines are all still the research focuses and development trends in meat quality nondestructive testing, so as to strictly ensure the quality and safety of commercial market meat.

So, this review provided a comprehensive summary of the current challenges and future research directions for meat quality detection tools based on the analysis, critical reviews, and synthesizing the findings of the recent articles on non-destructive technologies.

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Conflict of Interest

All the authors declare no conflict of interest.

Author Contributions

Xin Sun conceived the idea and designed the study. Jennifer Young, David Newman and Eric Berg performed the experiments and analyzed the data. Xiaochan Wang contributed to the design and interpretation of the study. Yinyan Shi and Borhan Mohammad wrote the manuscript.

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Tab.1 Recent studies on meat quality detection using computer vision system

Performance	References
Accuracy of 92.5%, 75.0%	(Sun et al., 2018)
Correlation coefficient of	(Taheri et al., 2019)
0.98734	
Correlation coefficient of 0.926	(Tappi et al., 2017)
Accuracy of 81.7%	(Chmiel et al., 2016a, b)
Error of 7.8%	(Mortensen et al., 2016)

Note: Support vector machine (SVM), genetic algorithm (GA), artificial neuronal network (ANN), analyses of variance (ANOVA), least significant difference (LSD), and multivariate linear regression (MLR).

Tab.2 Recent studies on meat quality detection using near-infrared spectroscopy

Category	Measured attribute	Analytical method	Performance	References
Chicken	Identification and classification (Moisture, lipid contents, protein contents, water holding capacity, and shear force)	SVM	Accuracy of 91.8%	(Geronimo et al., 2019)
Pork	Freshness	BP-AdaBoost	Correlation coefficient of 0.8325	(Huang et al., 2015)
Chicken	Water-holding capacity	PCA and PLSR	Correlation coefficient of 0.91	(Barbin et al., 2015)
Mutton	Discriminating the adulteration	SVM	Accuracy of 90.38-99.07%	(Zhang et al., 2015a)
Pork	Moisture	PLSR	Correlation coefficient of 0.906	(Peng et al., 2018)
Chicken breast	Protein	LDA and PLSR	Accuracy of 99.5-100%	(Wold et al., 2017)
Fish	Microbial spoilage	PLSR and LS-SVM	Correlation coefficient of 0.93	(Cheng et al., 2015a)
Rhubarb	Identification	PLS-DA, SIMCA, SVM and ANN	Accuracy of 94.12%	(Sun et al., 2017)
Beef	Adulteration	AF	Correlation coefficient of 0.91	(Chen et al., 2018)
Beef, chicken and lard	Authentication and classification	SVM	Accuracy of 98.33%	(Alfar et al., 2016)
Turkey meat	Identification	PLS-DA	Correlation coefficient >0.884	(Alamprese et al., 2016)

Note: BP-AdaBoost, namely back propagation artificial neural network (BP-ANN) and adaptive boosting (AdaBoost), linear discriminant analysis (LDA), partial least squares-discriminant analysis (PLS-DA), soft independent modeling of class analogies (SIMCA), least square support vector machines (LS-SVM), and artificial fish swarm algorithm (AF).

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Tab.3 Recent studies on meat quality detection using hyperspectral imaging (HSI) technique

Category	Measured attribute	Analytical method	Performance	References
Chicken meat	Texture	ACO-BPANN and PCA-BPANN	Correlation coefficient of 0.754	(Khulal et al., 2016)
Prawn	TVB-N (freshness)	PLSR, LS-SVM and BP-NN	Correlation coefficient of 0.9547	(Dai et al., 2016)
Beef	Total viable count (TVC) of bacteria (freshness)	PLS and LS-SVM	Accuracy of 97.14%	(Yang et al., 2017a)
Pork meat	Protein and TVB-N content	PLSR and LS-SVM	Correlation coefficient of 0.861	(Yang et al., 2017b)
Fish	Freshness	PCA and BP-ANN	Accuracy of 94.17%	(Huang et al., 2016)
Pork muscles	Intramuscular fat contents	SVM, SG, SNV, MSC and PLSR	Correlation coefficient of 0.9635	(Ma et al., 2018)
Frozen pork	Myofibrils cold structural deformation degrees	PLSR and SPA	Correlation coefficient of 0.896	(Cheng et al., 2018)
Lamb, beef, and pork	Adulteration	SVM and CNN	Accuracy of 94.4%	(Al-Sarayreh et al., 2018)
Beef	Adulteration	PLSR and SVM	Accuracy of 95.31%	(Ropodi et al., 2017)
Fish (grass carp)	Textural changes (Warner-Bratzler shear force, hardness, gumminess and chewiness)	PLSR	Correlation coefficient of 0.7982-Correlation coefficient of 0.8774	(Ma et al., 2017a)
Lamb meat	Adulteration	SPA and SG	Correlation coefficient above 0.99	(Zheng et al., 2019)
Pork	Intramuscular fat content	MLR	Correlation coefficient of 0.96	(Huang et al., 2017)
Pork *longissimus dorsi* muscles	Moisture content (MC)	PLSR	Correlation coefficient of 0.9489	(Ma et al., 2017b)
Grass carp (*Ctenopharyngodon idella*)	Moisture content	PLSR	Correlation coefficient of 0.9416	(Qu et al., 2017)
Lamb muscle	Discrimination	PCA, LMS, MLP-SCG, SVM, SMO and LR	Accuracy of 96.67%	(Sanz et al., 2016)
Beef	Adulteration	PLSR, SVM, ELM, CARS and GA	Correlation coefficient of 0.97	(Zhao et al., 2019)

Note: Principle component analysis (PCA), ant colony optimization (ACO), savitzky golay (SG)-smoothing, standard normal variate (SNV), multiplicative scatter correction (MSC) and partial least squares regression (PLSR), successive projections algorithm (SPA), convolution neural networks (CNN), artificial fish swarm algorithm (AF), linear least mean squares (LMS), multilayer perceptron with scaled conjugate gradient (MLP-SCG), sequential minimal optimization (SMO), logistic regression (LR), extreme learning machine (ELM), and competitive adaptive reweighted sampling (CARS).

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Tab.4 Recent studies on meat quality detection using Raman spectra technique

Category	Measured attribute	Raman frequency range	Analytical method	Performance	References
Grass carp surimi	Changes of protein structure and amino acid residue microenvironment	2900 cm^{-1}	/	Effective	(Gao et al., 2018)
Bull beef	Sensory characteristics (flavour)	1300-2800 cm^{-1}	PLSR	Correlation coefficient of 0.80-0.96	(Zhao et al., 2018)
Beef tallow, pork lard, chicken fat, duck oil	Adulteration (unsaturated fatty acids and total fatty acids)	700-1800 cm^{-1}	Correlated linear	Correlation coefficient of 0.96674 and 0.97148	(Lee et al., 2018)
Chicken	Sodium chloride or sodium bicarbonate	1659 ± 0.58 cm^{-1} to 1661 ± 0.58 cm^{-1}	one-way ANOVA	/	(Zhu et al., 2018)
Bovine	Tenderness (shear force)	800-1550 cm^{-1}	PLSR	Accuracy of 70-88%	(Bauer et al., 2016)
Lamb	Intramuscular fat content and major fatty acid groups	500-1800 cm^{-1}	PLSR and linear regression	Correlation coefficient of 0.93	(Fowler et al., 2015b)
Bovine serum albumin	Orientation of Norfloxacin	300-1800 cm^{-1}	/	/	(Lian et al., 2019)
Cooked meat	Endpoint temperature	1800-2000 cm^{-1}	PLS-DA and PCA	Accuracy of 97.87%	(Berhe et al., 2015)
Beef lions	Eating quality traits (juiciness and tenderness)	671 nm	PLSR	/	(Fowler et al., 2018)
Porcine meat	pH	323-2105 cm^{-1}	ACO	Correlation coefficient of 0.90	(Nache et al., 2016)

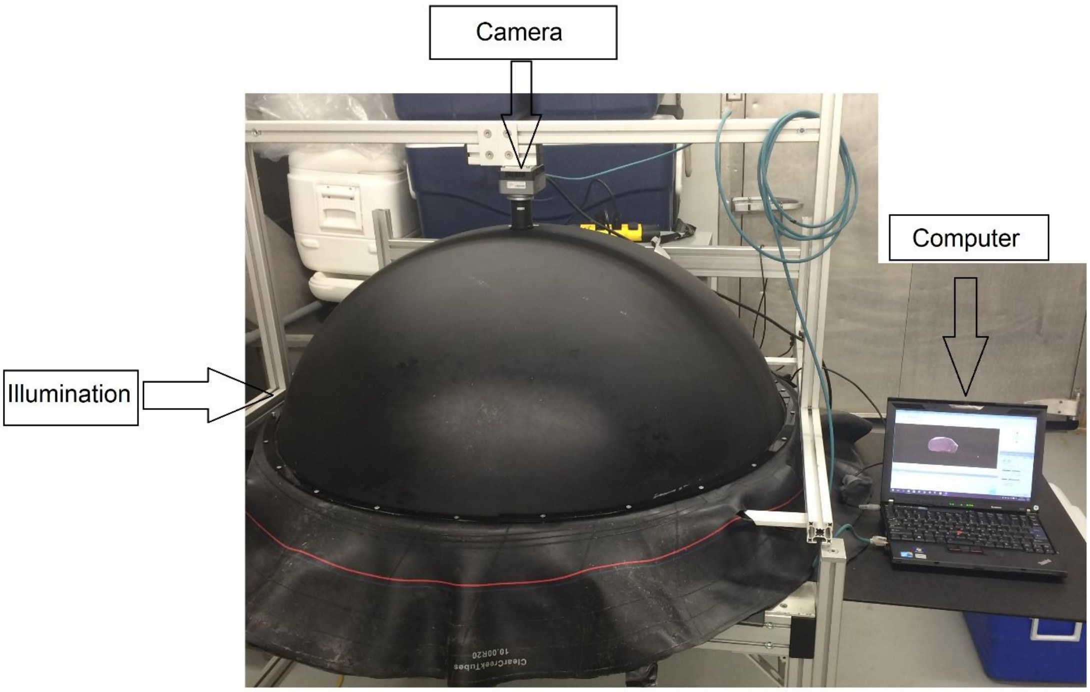
Figure legends

Fig. 1. Components of a meat computer vision system

Fig. 2. Components of a meat spectral detection system

Fig. 3. Hypercube information diagram of hyperspectral image for meat detection

ACCEPTED



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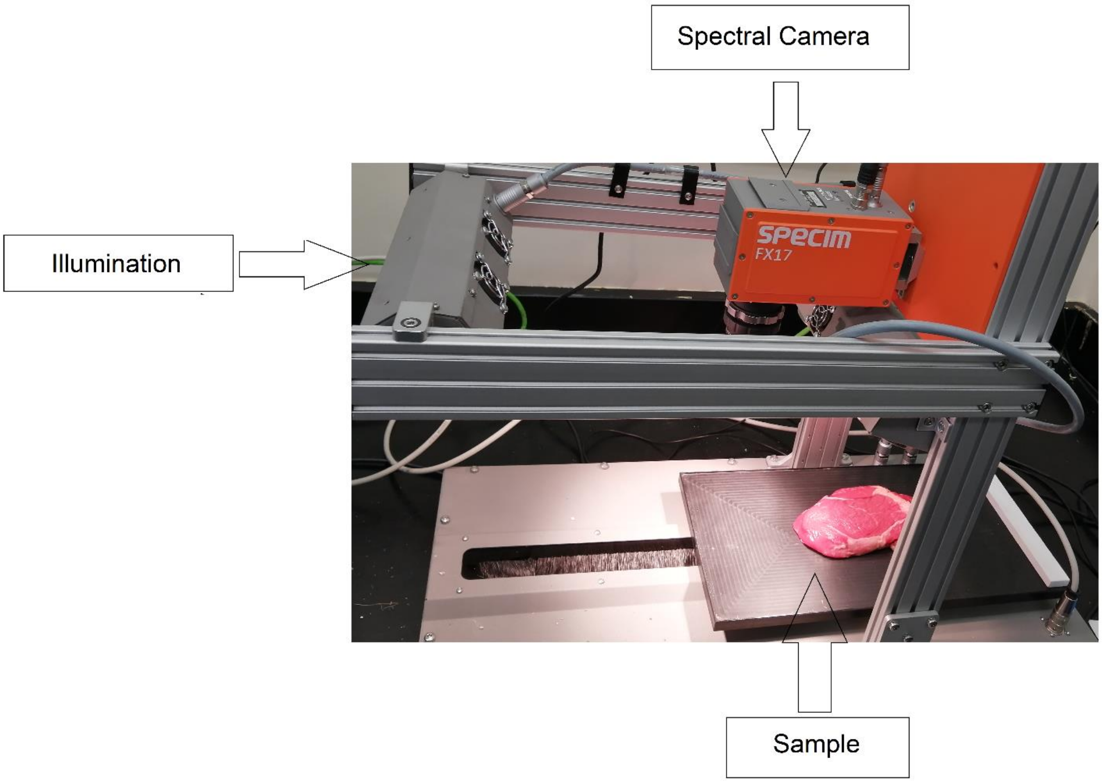

Fig. 2. Components of a meat spectral detection system

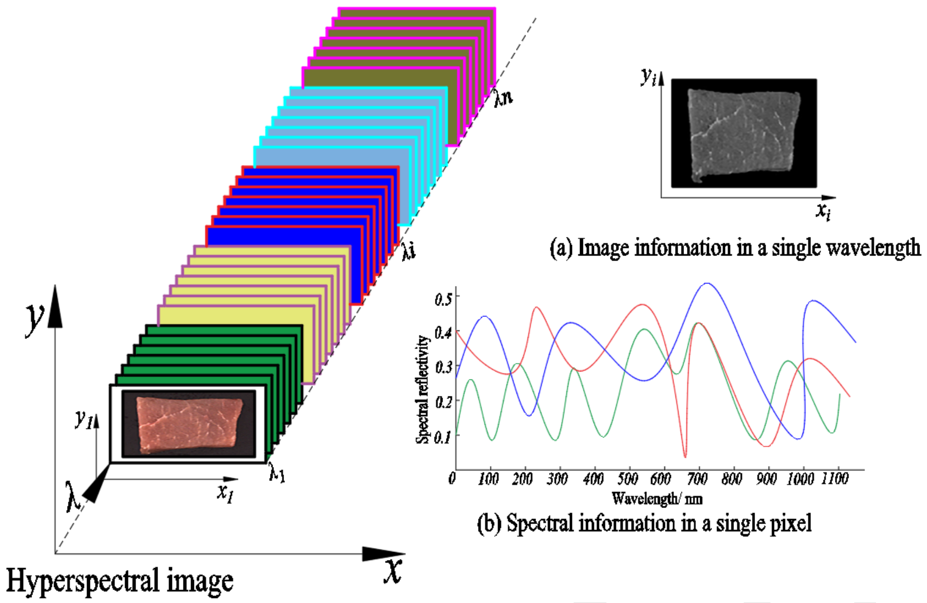

Fig. 3. Hypercube information diagram of hyperspectral image for meat detection