

## Review

# Non-Destructive Detection of Meat Quality: Sensing Information, Application Scenarios, and Multi-Source Fusion

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## Abstract

The growing demand for meat products has made quality and safety assessment a priority throughout production, processing, storage, distribution, and consumption. Meat quality encompasses sensory attributes, physicochemical properties, nutritional composition, microbial status, freshness, and safety-related characteristics. Conventional sensory, physicochemical, and microbiological methods provide reliable reference measurements, but they are generally time-consuming, labor-intensive, destructive, and unsuitable for real-time or online inspection. This review summarizes recent advances in non-destructive technologies for meat quality assessment, including spectroscopy, imaging and machine vision, odor and taste sensing, ultrasonic and electrical methods, low-field nuclear magnetic resonance, and multi-source information fusion. After outlining the fundamental principles and representative applications of each technology, this review further compares the types of sensing information they provide, the quality attributes they are suitable for assessing, their application scenarios, practical limitations, and model validation requirements. Current evidence indicates that these technologies have considerable potential for rapid screening, process monitoring, quality visualization, and intelligent evaluation. However, practical deployment still requires reliable reference measurements, representative calibration datasets, robust models, external validation, and standardization across instruments and production conditions. Future research should prioritize sensor miniaturization, calibration transfer, standardized datasets, explainable intelligent evaluation, and practically deployable multi-source fusion.

**Keywords:** meat quality; non-destructive detection; spectroscopy; hyperspectral imaging; electronic nose; multi-source information fusion

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## 1. Introduction

Meat and meat products are major dietary sources of protein, fat, vitamins, and minerals, and their quality is closely linked to food safety. As consumer expectations continue to evolve, attention in the meat industry has shifted from product availability to quality, safety, and traceability [1–3]. Meat quality, however, is affected by breed, slaughter

conditions, transportation, and storage [4–6]. These factors can contribute to nutrient degradation, quality deterioration, and microbial growth in meat products [7–9].

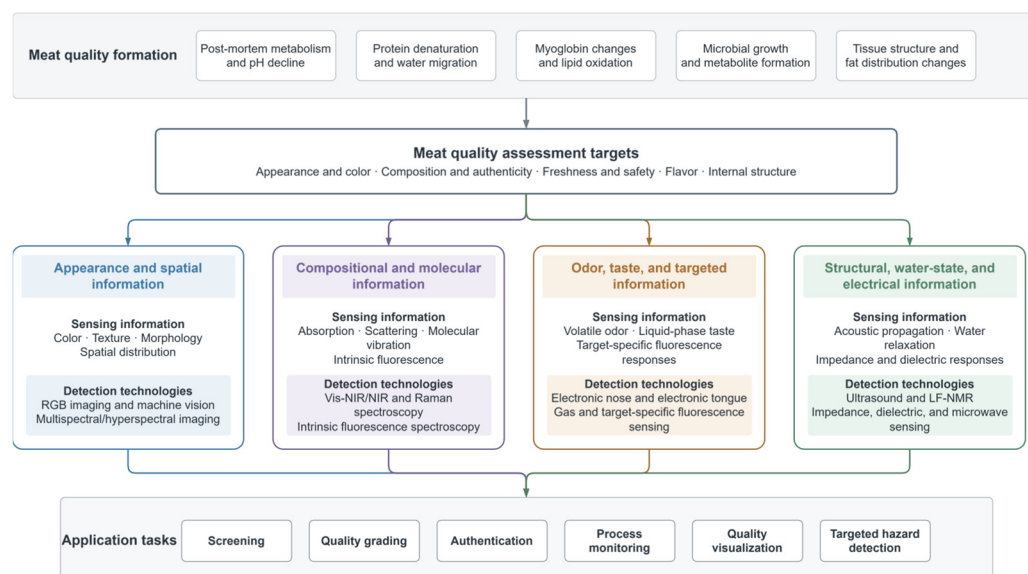
Conventional methods for assessing meat quality include sensory evaluation, physicochemical analysis, and microbiological testing. Although these methods provide reliable reference measurements, they are often time-consuming, labor-intensive, and destructive, which limits their use for real-time or online inspection during production, processing, distribution, and retail [10,11]. These constraints have driven the development of rapid, accurate, and non-destructive approaches for meat quality assessment [12,13].

Near-infrared spectroscopy, hyperspectral imaging, Raman spectroscopy, fluorescence spectroscopy, machine vision, electronic noses and electronic tongues, ultrasound, dielectric property measurements, and multi-source information fusion have been increasingly used to evaluate meat quality and safety [12–14]. These technologies capture quality-related information from spectral signals, imaging features, odor profiles, acoustic responses, and electrical properties, providing new routes for rapid and non-destructive assessment of meat quality and safety [15–17].

Previous reviews have examined non-destructive meat quality assessment from the perspectives of spectroscopy, hyperspectral imaging, machine vision, electronic noses, and multisensor systems. However, many have focused mainly on the principles or representative applications of individual technologies. Less attention has been given to the relationship between the information generated by different sensors and specific meat quality attributes, the comparative suitability of these technologies for different practical tasks, and the level of validation required before predictive models can support rapid screening, process monitoring, or industrial decision-making. Questions relating to model robustness, transferability across instruments and production conditions, and the need for and feasibility of multi-source information fusion also remain insufficiently addressed [18–20].

The literature discussed in this review was retrieved primarily from the Web of Science Core Collection, with the search updated through June 2026. The review focused on peer-reviewed studies involving non-destructive, minimally invasive, or sensor-assisted assessment of meat and meat products. Search terms included various combinations of “meat quality,” “meat safety,” “non-destructive detection,” “spectroscopy,” “visible/near-infrared spectroscopy,” “hyperspectral imaging,” “Raman spectroscopy,” “fluorescence sensing,” “machine vision,” “electronic nose,” “electronic tongue,” “ultrasound,” “impedance,” “dielectric properties,” “low-field nuclear magnetic resonance,” and “multi-source information fusion.” The selected studies covered major sensing technologies, target quality attributes, modeling approaches, validation strategies, and application scenarios. Methods that do not strictly fall within the scope of direct non-destructive detection, such as chromatographic analysis of volatile compounds and ultrasound-assisted processing, were included where they contributed to quality assessment, marker identification, or process monitoring.

Against this background, this review summarizes and compares the major non-destructive technologies used in meat quality assessment in terms of their fundamental principles, sensing information, representative applications, suitable quality attributes, practical limitations, model validation requirements, and application scenarios. It also examines the complementary value of different sensing modalities, the major levels of multi-source information fusion, the conditions under which fusion is justified, and the challenges involved in translating laboratory research into industrial practice. Figure 1 links the mechanisms underlying meat quality development with target quality attributes, sensing information, detection technologies, and application tasks, thereby providing a unified framework for comparing the technologies discussed in the following sections.



**Figure 1.** Framework for meat quality assessment targets and detection technology selection.

## 2. Spectroscopic Detection Technologies

Among the non-destructive approaches used for meat assessment, spectroscopic techniques are among the earliest developed and most widely applied. By measuring absorption, scattering, or fluorescence responses arising from interactions between light and meat, these techniques can provide information related to moisture, protein, fat, pigments, and selected safety-related attributes. The type and depth of information obtained depend on the spectroscopic modality. Visible–near-infrared and near-infrared spectroscopy primarily provide bulk compositional and optical information, Raman spectroscopy offers molecular fingerprint information, whereas fluorescence spectroscopy and fluorescence sensing can provide high sensitivity for selected analytes. This section reviews visible–near-infrared and near-infrared spectroscopy, Raman spectroscopy, and fluorescence-based methods, with particular attention to their applications and limitations in meat quality and safety assessment [7].

### 2.1. Visible–Near-Infrared and Near-Infrared Spectroscopy

Vis–NIR spectroscopy and near-infrared spectroscopy (NIRS) both obtain quality-related information by measuring the absorption and reflectance responses of meat samples at different wavelengths. The visible light region mainly reflects the color of meat and the state of myoglobin, while absorption in the near-infrared region mainly arises from the overtone and combination-band vibrations of chemical bonds such as C–H, O–H, and N–H, which can be used to characterize changes in components such as moisture, protein, and fat in meat. Owing to rapid spectral acquisition, minimal sample preparation, and non-destructive measurement, this type of spectral technology has been widely used in meat quality evaluation, authenticity assessment, and freshness monitoring [21,22]. Relevant reviews show that when combined with chemometric and machine learning methods, spectroscopic technology can extract information related to target quality indicators from complex spectral responses, but model performance still depends on the sample range, instrument type and validation strategy [23].

Portability and equipment cost are important factors promoting the use of near-infrared spectroscopy for on-site meat inspection [24–26]. With the development of microspectrometers, handheld devices and sensors connected to smart terminals, their application scenarios have gradually expanded from laboratory analysis to packaging, refrigeration, transportation and sales [27,28]. These devices increase the flexibility of field

measurements, but generally have narrower spectral ranges, lower resolution, and lower signal-to-noise ratios than laboratory instruments, and their adaptability to complex meat samples and environmental changes is also relatively limited. Therefore, portable near-infrared devices are currently more suitable for product screening, classification, and process monitoring and cannot yet fully replace laboratory-grade instruments [29,30].

In freshness evaluation, visible–near-infrared and near-infrared spectroscopy can be used both to identify the storage stage of meat and to predict quality indicators that change with the spoilage process. Wu et al. used Fourier transform near-infrared spectroscopy combined with AdaBoost-ULDA to classify pork samples by storage time and achieved a classification accuracy of 100% [31]. Analysis of the visible–near-infrared spectra of pork further showed that spectral changes during storage are related to factors such as myoglobin, fat, moisture and collagen [32]. On this basis, Ma et al. used 400–1700 nm visible–near-infrared spectroscopy to evaluate beef color, total volatile basic nitrogen (TVB-N), pH, and total viable count (TVC), showing that complementary color and composition signals can characterize meat freshness [33].

Similarly, Chen et al. used visible–near-infrared spectroscopy of 400–1800 nm with a resolution of 4 nm to simultaneously predict beef TVB-N and  $L^*$ ,  $a^*$ , and  $b^*$  parameters [12]; Jia et al. used near-infrared spectroscopy of 1000–2500 nm with a resolution of 0.96 nm to predict beef color changes, total myoglobin and its different chemical forms [22]. The former covers the visible light region and can directly obtain optical responses related to meat color; the latter uses a wider near-infrared range and higher spectral resolution to provide more detailed composition-related information. These two studies show that both the visible and near-infrared regions can be used for meat color evaluation, but the two spectral regions emphasize different types of information, and the specific spectral range should be selected based on the target indicators and instrument conditions. In general, the visible light region mainly provides information on meat color and myoglobin status, while the near-infrared region more strongly reflects changes in moisture and chemical composition. The combination of the two helps to evaluate the freshness of meat products from both color and composition.

In authenticity evaluation, existing studies have mainly used near-infrared spectroscopy for adulteration ratio determination, meat type identification and quality category discrimination. Tarcan and Kuplulu conducted a quantitative analysis of chicken adulteration in beef and beef sausages, and the established model showed strong calibration and validation performance [34]. Portable near-infrared spectroscopy can also use spectral differences between the carcass surface and subcutaneous fat to identify quality categories of Iberian pig carcasses [35]. For identification among multiple meat species, Mia et al. analyzed 1200 beef, goat and chicken samples and found that logistic regression and neural networks have good classification capabilities for both fresh and frozen meat [36]. In comparison, near-infrared spectroscopy achieved accuracies of 58.97–75.00% in detecting pork adulteration in beef balls [37]. These results show that the difficulty of authenticity detection not only depends on the compositional differences between meat types but is also affected by the processing method, sample morphology and spectral collection location. The classification model established on intact meat samples may not be directly applicable to minced or mixed meat products.

The practical application of visible–near-infrared and near-infrared spectroscopy still faces problems such as dependence on reference measurements and model applicability. Model development usually requires conventional physicochemical or microbiological measurements as a reference, and factors such as meat temperature, surface moisture, fat distribution, muscle type, storage time, animal breed and age will all affect the spectral response. Different studies have used methods such as multiplicative scatter correction (MSC), standard normal variate transformation (SNV), derivative processing, and

informative-wavelength selection to reduce the effects of scattering, baseline drift, and irrelevant variables [12,22]. However, the effectiveness of preprocessing is related to sample conditions, spectral range and target indicators, and still needs to be validated using independent data. Current evidence is insufficient to determine a unified optimal pretreatment method. In this context, robust spectral signatures and models should not only perform well in internal validations but also be adaptable to different batches, sample sources, instruments, and detection environments. Strengthening external validation, model transfer between instruments and performance evaluation under field conditions are key to improving the practical application value of this type of spectroscopic technology.

## 2.2. Raman Spectroscopy

Raman spectroscopy is a vibrational spectroscopic technique based on inelastic scattering generated by the interaction of light with sample molecules. By identifying the vibration modes of different chemical bonds, Raman spectroscopy can provide structural information related to meat proteins, fatty acids, pigments, and some metabolites, and can be used to analyze changes in meat composition, processing status, and quality attributes [38]. Compared with near-infrared spectroscopy, which mainly provides information related to the overall composition, Raman spectroscopy has strong molecular fingerprint characteristics and can provide more chemically specific structural information, so it can be used as a supplementary tool for meat quality evaluation [39].

Surface-enhanced Raman spectroscopy (SERS) uses metal nanostructures to enhance the Raman signal of the target analyte, further improving the detection sensitivity of Raman spectroscopy for specific substances [40]. For example, Zhang et al. used SERS to detect sulfathiazole in chicken blood and established a quantitative model in the range of 1–38 mg/L. The lowest experimentally detected concentration was 1 mg/L [41]. This result demonstrates that SERS can be used to detect analytes at low concentrations that are difficult to detect with conventional Raman signals. With the development of handheld and portable Raman equipment, Raman spectroscopy has become increasingly suitable for on-site inspection of meat products [42].

The application of Raman spectroscopy in meat analysis mainly involves composition characterization, processing status evaluation, meat color analysis, and safety testing. Studies have shown that a single Raman measurement can provide multidimensional information related to protein structure, fatty acid composition, sensory attributes, postmortem changes, and spoilage processes [38]. In terms of processing status evaluation, Narvaez et al. used spontaneous Raman spectroscopy to analyze the spatial differences in the endpoint temperature of cooked pork. Using principal component analysis-random forest (PCA-RF) and partial least squares (PLS), they achieved 87.5% classification accuracy and mapped cross-sectional temperature distributions [43]. For meat gels, Raman spectroscopy with uninformative variable elimination-support vector machine (UVE-SVM) predicted water-holding capacity and gel strength under different starch levels [44]. A convolutional neural network-long short-term memory (CNN-LSTM) model predicted gel strength and whiteness in heat-induced pork mince gels [45,46]. These studies demonstrate the ability of Raman spectroscopy not only to identify compositional differences but also to evaluate structural and functional properties developed during processing using changes in protein conformation and molecular interactions. The combination of Raman spectroscopy, infrared spectroscopy and chemometrics has also been used to analyze the fatty acid composition of animal-derived oils, showing the potential of complementary spectroscopic information in complex lipid systems, but its applicability in meat systems still needs further verification [47].

Raman spectroscopy can also explain changes in meat color at the molecular level. By extracting characteristic spectral features of different myoglobin forms, Raman

spectroscopy combined with the RF-PLS model enabled the simultaneous quantification of deoxymyoglobin and oxymyoglobin in pork, providing a basis for analyzing the formation and changes of meat color [48]. In terms of safety evaluation, relevant reviews show that SERS has been used to detect specific hazards such as bacteria, veterinary drug residues, illegal additives, and toxins [40]. In addition, Raman spectroscopy combined with artificial intelligence methods has also been used to assess the authenticity of minced meat, indicating that molecular fingerprint information can support the classification of different meat types and mixed meat samples [49]. Compared with composition and processing status evaluation, SERS safety testing usually relies on enhanced substrates, recognition elements or sample processing steps, and is therefore closer to targeted detection of specific hazards rather than a direct evaluation of the overall quality of meat.

Although Raman spectroscopy can provide clear molecular structure information, conventional Raman signals are weak and easily affected by sample fluorescence background, surface inhomogeneity, and collection conditions. SERS improves the sensitivity of target detection, but its actual operation may include steps such as sample extraction, centrifugation, filtration, enhanced substrate preparation, and target adsorption. For example, in the study reported in Ref. [41], the optimized adsorption time was 14 min, in addition to the time required for extraction and purification of chicken blood samples. Therefore, both the spectral acquisition time and the full analytical workflow need to be considered when evaluating its detection speed. Batch-to-batch variability of substrates, matrix interference in complex meat samples, and limited model stability across sample batches are still important factors limiting the field application of SERS. Future research should standardize collection conditions, improve substrate consistency, conduct multi-batch external validation, and develop portable equipment to improve the practical application value of Raman spectroscopy in meat quality and safety evaluation [40,42].

### 2.3. Fluorescence Spectroscopy and Fluorescence Sensing

Fluorescence spectroscopy and fluorescence sensing both obtain analytical information by measuring fluorescence intensity, emission peak position, fluorescence lifetime, or changes in the intensity ratio between different emission peaks, but their information sources and application methods are different [50–52]. Fluorescence spectroscopy mainly uses the endogenous signals of proteins, coenzymes, pigments, and other endogenous fluorophores in meat to analyze the composition, structure and changes that occur during storage [53–55]. Fluorescence sensing usually uses fluorescent probes, nanomaterials or specific recognition elements to convert changes in target concentration into fluorescence intensity or color changes. Therefore, the former can be used to evaluate meat freshness and authenticity, while the latter is more suitable for targeted detection of specific additives, contaminants or safety hazards [56].

In the overall quality evaluation of meat products, endogenous fluorescence spectroscopy can simultaneously reflect changes in multiple fluorescent substances and their surrounding microenvironment. Studies have used fluorescence spectroscopy combined with multivariate analysis to evaluate freshness indicators such as pork TVB-N, total bacterial count, and pH [55] and to identify turkey or chicken adulteration in ground beef [54,56]. For cooked ground beef, fluorescence spectroscopy can also detect compositional and structural differences caused by the incorporation of chicken [57]. These studies show that fluorescence spectroscopy can not only detect single fluorescent substances, but also make use of the overall fluorescence fingerprint observed across different meat types, processing states, and spoilage processes for classification or quantitative prediction. However, fluorescence fingerprints are affected by factors such as protein denaturation, lipid oxidation, pH, and sample surface state, and their models usually need to be calibrated for specific meat types and processing conditions.

Fluorescence sensing generally has greater target selectivity than endogenous fluorescence spectroscopy. Fluorescent probes, quantum dots, metal nanoclusters, and ratiometric fluorescence systems can convert target concentration changes into fluorescence intensity or color changes, and can be combined with microfluidic chips and smartphones to enable portable readout [50,51]. For example, Li et al. constructed a sausage nitrite detection system based on fluorescence resonance energy transfer between MoS<sub>2</sub> quantum dots and gold nanoclusters, with a fluorescence detection limit of 0.67 nM and a reaction time of 7 min [53]. Another study on ham nitrite detection obtained a fluorescence detection limit of 0.518 nM, but sample extraction was required, followed by a 5–20 min color-development period [58]. These results demonstrate the high sensitivity of fluorescence sensing to specific targets, and also indicate that its detection performance is closely related to the probe system, reaction conditions, and sample processing.

Fluorescence sensing is also used to detect microorganisms, antibiotic residues, and volatile spoilage markers. A reported fluorescent biosensor can be used for targeted detection of *Staphylococcus aureus* in pork and beef. The analysis time was approximately 30 min and the detection limit was 25 CFU/mL [52]. The ratiometric fluorescence method based on microfluidic paper chips and smartphones can provide an antibiotic-residue readout within 10 min, but this time does not include probe preparation and meat sample extraction processes [51]. For hydrogen sulfide and methyl mercaptan generated during putrefaction, the detection limits of the fluorescent film sensor are 224 and 233 nM, respectively [59]. Another hydrogen sulfide ratiometric fluorescent paper sensor has a lower detection limit, but its signal does not stabilize until 48 h of exposure [50]. Therefore, the sensitivity and detection speed of different methods need to be evaluated in conjunction with specific operating procedures.

The main advantages of fluorescence methods are high sensitivity, readily interpretable or visually readable signals, and the potential for visualization and portable reading, but their applicability often depends on the target, fluorescent material, and recognition system. Intrinsic fluorescence spectroscopy can obtain an overall fluorescence fingerprint without damaging the sample, but its selectivity and detection sensitivity may be limited by the complex meat matrix. Probe-based fluorescence sensing is a further extension of the principle of fluorescence detection. This approach improves selectivity and sensitivity to the target analyte, although it may require small-volume sampling, sample extraction or specific reaction. Such methods can therefore serve as a highly sensitive complement to non-destructive quality screening for further identification of specific safety hazards. Future research should focus on simplifying the sample-preparation procedure, improving the stability and batch-to-batch consistency of fluorescent materials, and promoting the application of fluorescence methods in on-site quality and safety screening through validation using complex meat matrices, multiple sample batches, and actual production conditions. Representative applications of these spectroscopic technologies are summarized in Table 1.

**Table 1.** Representative applications of spectral detection technology in meat quality and safety evaluation.

| Technology                             | Sample                      | Sample Size                                           | Target Variable/Application                                       | Spectral Range or Raman Shift | Method/Model         | Ref. |
|----------------------------------------|-----------------------------|-------------------------------------------------------|-------------------------------------------------------------------|-------------------------------|----------------------|------|
| visible–near-infrared spectroscopy     | beef                        | 420 meat samples                                      | Freshness, TVB-N, and L*, a*, b* predictions                      | 400–1800 nm                   | PSOGA-XGBoost        | [12] |
| near-infrared spectroscopy             | beef                        | 216 meat samples                                      | Prediction of meat color, total myoglobin and its different forms | 1000–2500 nm                  | PLSR, SVM            | [22] |
| near-infrared spectroscopy             | chicken breasts and legs    | 324 prepared meat samples                             | Tenderness and shear force prediction                             | 662–1005 nm                   | PCNN, LVNN, PCR, PLS | [60] |
| near-infrared spectroscopy             | chicken breasts and legs    | 324 prepared meat samples                             | Tenderness and shear force prediction                             | 662–1005 nm                   | PCR, PLS             | [61] |
| visible–near-infrared spectral imaging | pork belly                  | 182 meat samples                                      | Hardness, fat content and chemical composition prediction         | 386–1015 nm                   | PLSR                 | [62] |
| near-infrared spectroscopy             | beef                        | 8 meat cubes                                          | Monitoring ice crystal formation during super-cooling             | 950–1650 nm                   | MSPC                 | [63] |
| visible–near-infrared spectroscopy     | yak meat                    | 36 meat samples                                       | Identification of grazing and house-raised yak meat               | 400–2500 nm                   | PLS-DA, SIMCA        | [64] |
| visible–near-infrared spectroscopy     | different beef muscles      | 240 muscle samples                                    | Classification of different muscle parts                          | 380–1028 nm                   | PLS-DA               | [65] |
| visible light spectrum                 | frozen pork                 | 144 meat samples                                      | Myoglobin content detection                                       | 622–770 nm                    | Si-CARS-PLS          | [66] |
| visible–near-infrared spectroscopy     | frozen and thawed pork      | 110 meat samples                                      | Cooking loss prediction                                           | 344–1032 nm                   | PLS, CARS-PLS        | [67] |
| Vis–NIR/NIR spectroscopy               | aged beef                   | NR                                                    | Evaluation of effects of freezing time and freeze–thaw cycles     | 400–2500 nm                   | ASCA                 | [68] |
| visible–near-infrared spectroscopy     | mutton                      | 150 meat samples                                      | Protein, fat, and moisture content prediction                     | 400–1700 nm                   | PLSR, MLR            | [69] |
| near-infrared spectroscopy             | beef carcass                | 829 carcasses                                         | Online prediction of marbling                                     | 740–1070 nm                   | RF                   | [70] |
| near-infrared spectroscopy             | pork fat                    | 46 samples (33 for calibration, 13 for validation)    | Authenticity assessment of pork products                          | 800–2500 nm                   | DD-SIMCA             | [71] |
| near-infrared spectroscopy             | sauce-braised meat products | 97 meat samples                                       | Fat, protein, collagen, ash, and sodium content prediction        | 650–950 nm and 960–1660 nm    | PLSR                 | [72] |
| near-infrared spectroscopy             | beef and other meats        | 16 meat samples (4 animals × 4 biological replicates) | Meat-species authentication                                       | 950–1600 nm                   | PCA, LDA, SI         | [73] |

|                                     |                                |                                                   |                                                                       |                                                                                                            |                                                               |      |
|-------------------------------------|--------------------------------|---------------------------------------------------|-----------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------|------|
| Raman spectrum                      | ground pork, beef and lamb     | 19 mixture-ratio samples                          | Authenticity assessment of minced meat and mixed meat                 | 200–3200 cm <sup>-1</sup> ; 785 nm excitation                                                              | SVM, ANN, RF                                                  | [49] |
| Raman spectrum                      | chicken and different tissues  | 1 chicken; 3 replicates per tissue                | Differentiating muscle and tissue types                               | 200–3200 cm <sup>-1</sup>                                                                                  | DFA                                                           | [74] |
| Raman spectrum                      | beef                           | 100 meat samples                                  | Prediction of metmyoglobin content and metmyoglobin-reducing activity | 400–1700 cm <sup>-1</sup>                                                                                  | PLSR                                                          | [75] |
| Raman spectrum                      | beef                           | 110 meat samples                                  | WBSF, intramuscular fat, drip loss, and cooking loss predictions      | 700–3100 cm <sup>-1</sup>                                                                                  | PLS                                                           | [76] |
| Raman spectrum                      | pork mince gel                 | 200 samples                                       | Gel strength and water-holding capacity prediction                    | 400–3200 cm <sup>-1</sup> ; 532 nm excitation                                                              | PLS                                                           | [77] |
| surface-enhanced Raman spectroscopy | chicken blood                  | 120 chicken blood samples                         | Sulfathiazole residue detection                                       | Acquisition range 150–2100 cm <sup>-1</sup> ; Analysis range 400–1800 cm <sup>-1</sup> ; 785 nm excitation | air-PLS, MSC, GA-SVR                                          | [41] |
| fluorescence spectrum               | ground beef and turkey         | 11 levels of adulteration                         | Turkey meat adulteration detection                                    | Excitation range 200–500 nm; Emission wavelength 525 nm                                                    | PLSR                                                          | [54] |
| fluorescence spectrum               | pork                           | 60 meat samples                                   | TVB-N, total bacterial count, and pH prediction                       | Excitation at 365 nm; emission range approximately 400–1000 nm                                             | PLSR                                                          | [55] |
| fluorescence spectrum               | ground beef and chicken        | 144 mixed meat samples                            | Chicken adulteration detection                                        | Fixed excitation wavelengths 290, 322 and 340 nm; Emission wavelength 410 nm                               | PLSR, HCA                                                     | [56] |
| fluorescence spectrum               | cooked ground beef and chicken | 11 independently proportioned samples; 99 spectra | Chicken adulteration detection                                        | Excitation wavelengths 290, 322 and 340 nm; Emission range 305–600 nm                                      | PCA, PLSR                                                     | [57] |
| fluorescence sensing                | beef                           | NR                                                | Freshness test                                                        | Excitation range 340–400 nm; Emission range 410–550 nm                                                     | Ratiometric fluorescent-film sensing/signal-response analysis | [59] |
| fluorescence sensing                | meat products                  | 7 samples                                         | Nitrite detection                                                     | Excitation at 365 nm; read signal at approximately 538 nm                                                  | Fluorescence sensing/signal response analysis                 | [58] |
| fluorescence sensing                | pork                           | NR                                                | Antibiotic residue detection                                          | Excitation wavelength approximately 360–365 nm; emission                                                   | Ratiometric fluorescence sensing/smartphone readings          | [51] |

wavelengths 445  
and 675 nm

Abbreviations: TVB-N, total volatile basic nitrogen; WBSF, Warner–Bratzler shear force; PLSR, partial least squares regression; SVM, support vector machine; PCA, principal component analysis; PLS-DA, partial least squares discriminant analysis; SIMCA, soft independent modeling of class analogy; RF, random forest; ANN, artificial neural network; HCA, hierarchical cluster analysis; SI, similarity index; NR, not reported. Spectral range and Raman shift are expressed in nm and  $\text{cm}^{-1}$ , respectively.

### 3. Imaging and Machine-Vision Detection Technologies

Imaging and machine-vision technologies provide an important means for meat appearance evaluation, quality grading and quality visualization by collecting meat sample images and extracting features such as color, texture, morphology, and spatial distribution. Based on their spectral dimensionality, related technologies mainly include RGB imaging, multispectral imaging and hyperspectral imaging. RGB imaging mainly obtains color and morphological information on the surface of meat samples; multispectral imaging uses a small number of discrete bands to obtain optical features related to specific quality attributes, showing application potential in meat type identification and spoilage evaluation [14,65]. Hyperspectral imaging combines continuous spectral information with spatial information to characterize the composition changes and spatial differences of meat samples [78].

#### 3.1. Hyperspectral Imaging

Hyperspectral imaging (HSI) combines spectral analysis with image acquisition to form a three-dimensional data cube containing two spatial dimensions and one spectral dimension by acquiring reflectance images across contiguous narrow spectral bands [79]. In meat assessment, HSI can obtain spectral responses related to moisture, protein, fat, pigments, and spoilage-related substances, while reflecting the spatial distribution of these responses on the surface of the meat sample [80,81]. As a result, the technology has been used to evaluate meat quality, freshness, safety and authenticity [82–84].

Compared with single-point spectra, the main feature of HSI is that it can provide composition-related information and spatial distribution information simultaneously. Single-point near-infrared spectroscopy mainly reflects the spectral characteristics of a single measurement point or an averaged region, while HSI can show the quality differences among different regions on the surface of the meat sample [85,86]. This feature makes it suitable for spatial heterogeneity analysis of meat products, visualization of quality indicators, identification of adulteration distribution, and process monitoring. Existing reviews have summarized the application of HSI in the quality evaluation of chicken, mutton, goat meat and other meat products, indicating that it has great potential in meat safety evaluation, quality grading and online monitoring [87,88].

In freshness and spoilage evaluation, HSI is mainly used to predict indicators such as TVB-N, total bacterial count, pH, dominant spoilage bacteria, and meat color [89–92]. Jiang et al. used 900–1700 nm near-infrared hyperspectral data to predict counts of *Pseudomonas* and *Enterobacteriaceae* in refrigerated chicken breasts, and the MSC-PLS model showed good predictive performance [90]. Achata et al. used visible–near-infrared HSI combined with chemometrics to predict microbial growth in beef under different refrigeration temperatures. Data fusion further improved the model performance [91]. In the evaluation of pork freshness, Sun et al. combined two-dimensional correlation spectral images with two-branch convolutional neural networks to establish a TVB-N prediction model [92]. These studies show that HSI can evaluate freshness by capturing combined changes in color, composition, and spatial distribution during meat spoilage, but the

model still requires traditional physicochemical or microbiological methods to provide reliable reference values [93].

In freeze–thaw identification and process monitoring, HSI can classify meat samples in different states and display spatial differences in quality changes. A related review shows that spectroscopy and imaging methods can use information such as moisture migration, protein changes, and oxidation status to evaluate the impact of freezing and thawing on meat quality [94–96]. In process monitoring, HSI is also used to evaluate the quality changes of surimi gel after cold plasma treatment [97] and to analyze the diffusion behavior of sucrose in cured beef and the absorption process of sodium chloride in pork [98,99]. During the beef drying process, Achata et al. used near-infrared HSI and chemometrics to compare spectral changes under different soaking treatments and drying times, showing the potential of HSI as a processing analysis tool [100]. Spectral and multiscale analysis were also used to identify critical quality deterioration stages during the microwave-vacuum drying process of *Macrobrachium rosenbergii* meat, providing a reference for processing monitoring of animal-derived muscle foods [101]. Yu et al. developed a relatively low-cost HSI system and combined it with classifiers such as SVM to distinguish fresh beef, frozen beef and frozen–thawed beef [102].

For frozen and thawed pork, Cheng et al. used HSI combined with a multi-task convolutional neural network to simultaneously monitor lipid and protein oxidation [103] and then compared the predictive performance of fluorescence HSI and visible–near-infrared HSI on thiobarbituric acid reactive substances (TBARS) [104]. Fluorescence HSI was also used to display the spatial changes in carbonyl and total sulfhydryl content to evaluate the distribution characteristics of protein oxidation during the freezing and thawing process [105]. Tian et al. combined HSI with confocal laser scanning microscopy to analyze the changes in microstructure and moisture distribution during the processing of dry-cured pork [106]. The application of vibrational spectroscopy in monitoring non-thermally processed meat products and protein gels also provides supporting evidence for optical methods to evaluate processing quality [46].

In adulteration and authenticity evaluation, HSI can not only perform classification and quantitative prediction, but also convert model results into spatial distribution maps. Jiang et al. used HSI combined with chemometrics to identify substitution of pork and duck in raw and cooked mutton rolls [107]. Relevant studies have shown that HSI can simultaneously provide information related to substance type, content and spatial location, and is therefore suitable for meat product authenticity evaluation [108]. Jiang et al. used 400–1000 nm HSI to detect jowl-meat adulteration in pork, and used SNV-PLSR to predict and display the adulteration ratio [109]. Liu et al. used a cascade wavelength selection strategy to quantitatively analyze pork and duck meat adulteration in recombinant steaks, showing that characteristic wavelength screening can reduce data dimensionality while retaining key information [110]. HSI combined with transfer learning has also been used to detect starch adulteration in chicken mince [111]. A VGG16–SVM model was used to identify soy protein in chicken mince [112]. These studies show the application potential of HSI in complex mixed meat samples, but pixel-level prediction maps are model-derived estimates, and their reliability depends on the reference value and model stability.

The practical application of HSI is still limited by equipment cost, data size and model applicability. Hyperspectral systems usually include light sources, imaging spectrometers, cameras, and computing platforms, and their equipment and maintenance requirements are higher than those of ordinary spectral or RGB machine vision systems. High-dimensional spatial–spectral data will also increase the storage and computing burden, while characteristic-wavelength selection, region-of-interest optimization, and lightweight models can improve processing efficiency [113,114]. In addition, the surface state of the meat sample, fat and muscle distribution, temperature, batch differences,

instrument parameters, and acquisition environment will affect the image and spectral response. Deep learning can enhance spatial-spectral feature extraction, but its performance still depends on the number of independent samples, data partitioning, and external validation. Future research should strengthen model evaluation in multiple batches, across instruments, and under actual production conditions, and promote the development of informative-band selection, simplified imaging systems, model transfer, and lightweight algorithms [115].

### 3.2. RGB Imaging and Machine Vision

RGB imaging obtains information on the red, green, and blue color channels of the meat sample using a camera, and uses machine vision methods to extract features such as color, shape, texture, and surface appearance [116,117]. This technology can convert manually observed appearance attributes into quantitative image parameters for meat appearance inspection, quality grading and automated identification. Relevant research shows that machine vision can automate part of the manual visual inspection process and reduce subjective differences in meat color and morphology evaluation [118,119].

Compared with MSI and HSI, the RGB machine vision system has a simpler structure, lower equipment cost and faster image acquisition. It is suitable for evaluating meat color, marbling, fat distribution, appearance integrity, and surface defects. RGB images can directly reflect the color, texture, and morphology of the surface of meat samples, but do not contain continuous spectral information, so their ability to characterize internal chemical composition and nonvisual safety attributes is limited.

RGB machine vision can either use hand-crafted image features or be combined with deep learning for automatic feature extraction. Traditional methods usually first perform background segmentation and region of interest extraction, then calculate features such as color, texture, morphology, and fat distribution, and use machine learning to complete classification or prediction. Deep learning can learn multi-level features directly from images, reducing reliance on hand-crafted feature design, but does not expand the underlying information content of RGB images itself. Therefore, model selection should consider the sample size, target attributes and actual application scenarios.

Machine vision is particularly suitable for evaluating attributes that can be directly observed on the surface of meat samples, such as marbling, fat distribution, meat color, and appearance defects. Meat marbling is closely related to consumer acceptance and eating quality [120]. Campos et al. developed a computer vision system for segmentation of marbling images and quantification of fat area and texture [121]. The study used a variety of devices to collect 82 images of 41 longissimus dorsi muscle samples, with a segmentation accuracy of over 98%, indicating that RGB machine vision can help standardize marbling and appearance quality evaluation and reduce subjective differences caused by manual grading.

However, RGB machine vision is easily affected by factors such as lighting, background color, shooting angle, surface moisture, and camera parameters. Therefore, standardized image acquisition conditions are the basis for ensuring the repeatability of color and texture features. The applicability of the model under different meat sample batches, cameras, and actual production conditions also needs further validation.

In general, RGB imaging is suitable for low-cost surface appearance evaluation, MSI can use a small number of discrete bands to supplement optical information other than color, and HSI can provide more complete spectral and spatial distribution information. The three differ in information dimensionality, device complexity, and application scenarios. Table 2 summarizes representative applications of HSI, MSI, and RGB machine vision. Imaging technology mainly relies on the optical response of meat samples, and the characterization of volatile odors, tastes, and other invisible sensory changes formed

during storage and processing is still limited. Odor and taste sensing technologies will be further discussed in the next section.

**Table 2.** Representative applications of imaging and machine vision technology in meat quality and safety evaluation.

| Imaging Type | Sample                      | Sample Size                                                                         | Target Variable/Application                                                           | Band Range or Image Information                   | Method/Model                                                                    | Ref.  |
|--------------|-----------------------------|-------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|---------------------------------------------------|---------------------------------------------------------------------------------|-------|
| HSI          | pork belly                  | 182 meat samples                                                                    | Hardness, fat content, and chemical composition prediction                            | 386–1015 nm                                       | Robust regression, PLSR                                                         | [62]  |
| MSI          | different beef muscles      | 240 muscle samples; 4560 images                                                     | Classification of different muscle types                                              | 19 discrete bands, approximately 405–1050 nm      | 2T2D-COS, PLS-DA                                                                | [65]  |
| HSI          | chicken breast              | 12 chicken breasts                                                                  | Detection of foreign matter on the surface of poultry meat                            | Acquisition 1000–2500 nm; model uses 1000–1700 nm | Semi-supervised GAN; FP16 post-training quantization; TensorRT GPU acceleration | [13]  |
| HSI          | chicken breast              | 120 meat samples (15 samples per day for 8 days)                                    | Prediction of freshness, total bacterial count, TVB-N, pH, and oxidation indicators   | 400–1000 nm                                       | PLSR, SVM, SVR                                                                  | [89]  |
| HSI          | pork                        | 70 half carcasses                                                                   | Pork belly cooking loss prediction                                                    | Acquisition 350–1002 nm, modeling 402–1002 nm     | PLSR                                                                            | [122] |
| HSI          | beef and pork mixture       | 9 levels of adulteration                                                            | Quantitative detection of pork adulteration in beef                                   | 894–2504 nm                                       | PLSR, VIP wavelength selection                                                  | [123] |
| HSI          | pork                        | 180 meat samples                                                                    | Freshness, microbiology, texture, and volatile components evaluation                  | Acquisition 308–1105 nm; Modeling 400–1000 nm     | Wavelet transform, SVM, SVR                                                     | [124] |
| HSI          | beef and adulterant tissues | 166 samples                                                                         | Low-level beef adulteration detection                                                 | 900–1700 nm                                       | PLS-DA, SVM-DA, RF                                                              | [125] |
| HSI          | beef                        | 23 steaks from 23 cows                                                              | Identification of water-holding capacity, texture, and feeding methods                | 900–1700 nm                                       | PLS-DA, RBF-SVM                                                                 | [126] |
| SWIR-HSI     | mutton                      | 210 meat samples; a total of 420 sets of HSI records before and after contamination | Foodborne pathogenic bacteria contamination status, type, and concentration detection | 1000–2500 nm                                      | PLSR, SVM, SVR                                                                  | [127] |
| HSI          | beef and adulterated meat   | 160 samples                                                                         | Meat authenticity evaluation                                                          | Vis–NIR: 400–1000 nm; SWIR: 1116–1670 nm          | SVM, SVR, RF                                                                    | [128] |
| HSI          | vacuum packed pork sausage  | 32 treatment groups                                                                 | Evaluation of antioxidant activity of modified casing sausages                        | 380–1100 nm                                       | PCA, PLSR                                                                       | [129] |
| HSI          | beef                        | Experiment 1: 160 samples;                                                          | Beef doneness evaluation                                                              | 400–1000 nm                                       | PCA, PLS-DA                                                                     | [130] |

|                          |                                 |                                                                              |                                                                    |                                                         |                                                                    |       |
|--------------------------|---------------------------------|------------------------------------------------------------------------------|--------------------------------------------------------------------|---------------------------------------------------------|--------------------------------------------------------------------|-------|
| Experiment 2: 32 samples |                                 |                                                                              |                                                                    |                                                         |                                                                    |       |
| NIR-HSI                  | beef                            | 360 meat samples from 20 cattle and 4 slaughter lots                         | Alanine content prediction                                         | 900–1700 nm                                             | 2D-COS, CARS, PLSR                                                 | [131] |
| NIR-HSI                  | chicken breast                  | 127 meat samples                                                             | Inosinic acid content prediction                                   | 900–1700 nm                                             | MAS-PLS, CARS-PLS                                                  | [132] |
| NIR-HSI                  | 4 types of chicken              | 120 chickens, 30 of each breed; 240 hyperspectral images in total            | Chicken breed identification                                       | 400–1000 nm                                             | PLS-DA, SVM, RF                                                    | [133] |
| NIR-HSI                  | beef                            | 58 meat samples                                                              | Tenderness classification                                          | 900–1700 nm                                             | PLS-DA                                                             | [134] |
| SWIR-HSI                 | mutton and adulterated mixtures | 192 samples                                                                  | Mutton adulteration detection under flavor interference conditions | 1000–2445 nm                                            | SVM, RF, sparrow search algorithm                                  | [135] |
| HSI                      | beef and adulterated mixtures   | 180 samples                                                                  | Beef adulteration detection                                        | 431–962 nm                                              | ICA, PLSR                                                          | [136] |
| dual-band HSI            | chicken breast                  | 240 samples                                                                  | Simultaneous evaluation of TVB-N and total bacterial count         | 397–1003 nm and 935–1720 nm                             | Multi-task transformer, attention                                  | [137] |
| Vis/NIR-HSI              | pork                            | 50 meat samples; a total of 100 sets of HSI data on the front and back       | Physicochemical indicators and sensory quality prediction          | 400–1000 nm and 900–1700 nm                             | SVM, RF, LR, SVR                                                   | [138] |
| Hyperspectral microscopy | pork                            | 90 meat samples                                                              | Freshness rating                                                   | 316–1111 nm                                             | PCA, GLCM, FDA, LDA, SVM, BP-ANN                                   | [139] |
| HSI                      | chicken                         | 75 meat samples                                                              | Quantitative prediction of TVB-N content                           | Acquisition: 430–960 nm; analysis: 490–900 nm           | PCA, ACO, BP-ANN                                                   | [140] |
| RGB machine vision       | chicken sausage                 | 40 sausage samples                                                           | Physicochemical quality and microbiological safety evaluation      | RGB color and surface image characteristics             | SVM                                                                | [141] |
| RGB machine vision       | beef                            | 30 meat samples; a total of 60 sets of color images before and after storage | Meat color changes and freshness evaluation                        | RGB, HSV and CIELAB color characteristics               | Decision tree, logistic regression, white-box classification model | [142] |
| RGB machine vision       | chicken                         | 200 images (100 each fresh and non-fresh)                                    | Chicken freshness identification                                   | RGB color moment characteristics                        | SVM                                                                | [143] |
| RGB machine vision       | mutton and adulterated mixtures | Modeling data 960 images; external validation 120 samples                    | Mutton authenticity assessment                                     | RGB front and back images                               | AlexNet, GoogLeNet, ResNet, VGG and other CNNs                     | [144] |
| RGB machine vision       | beef                            | Longissimus dorsi muscle samples from 45 carcasses                           | Beef quality evaluation                                            | RGB color, morphology and surface image characteristics | Statistical analysis                                               | [145] |

Abbreviations: HSI, hyperspectral imaging; MSI, multispectral imaging; SWIR-HSI, short-wave infrared hyperspectral imaging; NIR-HSI, near-infrared hyperspectral imaging; RGB, red, green, and blue three-channel imaging.

## 4. Odor and Taste Sensing Technologies

Meat produces a complex mixture of volatile compounds and taste-related components during storage, processing, and spoilage. This information is difficult to fully characterize through spectroscopy or imaging techniques. Odor- and taste-sensing technologies convert meat flavor, freshness, and spoilage processes into analyzable sensing signals by capturing volatile compounds, water-soluble flavor substances or overall odor fingerprints [146,147]. This section discusses the application of electronic noses and electronic tongues, volatile components and odor fingerprint analysis in meat quality evaluation.

### 4.1. Electronic Nose and Gas-Sensor Arrays

An electronic nose (E-nose) usually consists of a gas-sensor array, a signal acquisition module and a pattern recognition algorithm. Volatile organic compounds released during storage, processing or spoilage of meat interact with the sensor array, generating electrical signals that reflect the overall odor characteristics [148–150]. Microbial metabolism, lipid oxidation, and protein degradation produce volatile substances such as amines, aldehydes, ketones, alcohols, and sulfur-containing compounds [151,152], so the electronic nose can use the overall odor fingerprint to evaluate the freshness, spoilage, authenticity, and processing quality of meat [153–155].

Compared with near-infrared spectroscopy, HSI and RGB machine vision, electronic noses mainly obtain volatile odor information released by meat products, which can address the limited characterization of spoilage odors and flavor changes by optical methods. Electronic noses usually do not require complex chemical extraction of meat samples, are relatively simple to operate, and are suitable for on-site screening of freshness, spoilage/off-odor, remaining shelf life, and adulteration [156]. However, electronic nose sensors usually respond to multiple volatile substances at the same time, and their output mainly reflects the overall response pattern of the mixed gas rather than a direct quantitative measurement of an individual compound. Therefore, model interpretation and stability are closely related to the sensor combination, headspace sampling conditions, and calibration samples.

In authenticity evaluation, electronic noses can utilize the overall odor differences between samples of different meat types or adulteration levels for classification. Ensemble learning methods have been used to optimize multiclass identification of pork adulteration in beef [157]. Sarno et al. used sensor array optimization, principal component analysis and support vector machine parameter optimization to detect pork adulteration in beef for halal authentication, and the classification accuracy reached 98.10% [158]. In meat quality evaluation, electronic nose data from different beef parts combined with feature dimensionality reduction and machine learning can be used for quality grade classification [159]. These results show that the electronic nose can identify odor differences formed by meat type, part, and storage state, but the high classification accuracy obtained on a single dataset still needs to be further verified by samples from different batches and sources.

In terms of sensing materials, polyaniline-based flexible sensors with trimethylamine as the target gas can be used alongside TVB-N measurements to evaluate the spoilage status of pork, showing the potential of low-cost gas sensors for freshness screening [160]. Headspace solid-phase microextraction-gas chromatography-mass spectrometry (HS-SPME-GC-MS) identified pork-storage volatiles that support gas-sensor selection and electronic-nose response interpretation [161]. For processed meat products, the formation of volatile organic compounds is affected by many factors such as raw material

composition, heating methods, lipid oxidation, amino acid degradation, and microbial metabolism. Therefore, the electronic nose model also needs to consider odor differences caused by processing technology and storage conditions [162].

Electronic noses are suitable for rapid screening of meat freshness, spoilage, adulteration and odor quality, but their responses are easily affected by sample temperature, ambient humidity, headspace equilibrium time, gas flow rate, and sensor aging. There may also be differences in sensor composition and response characteristics across devices, limiting the direct application of models across batches, instruments, and production environments. Future research should strengthen the standardization of headspace sampling and sensor arrays, develop humidity- and drift-resistant sensing materials, and conduct model validation across batches, equipment, and actual storage conditions.

#### 4.2. Electronic Tongue and Taste Sensing

An electronic tongue (E-tongue) uses a multi-sensor array to respond to soluble flavor substances, ionic composition and other taste-related components in the sample, and combines multivariate analysis or machine learning to evaluate taste attributes, processing status, freshness, and shelf life. Unlike electronic noses, which mainly obtain volatile odor information, electronic tongues focus more on taste substances in the liquid phase, which can supplement taste information that is difficult to provide by odor sensing and optical detection [163].

Electronic tongues are mainly suitable for products where water-soluble taste substances have an important impact on quality, such as marinated, pickled, fermented and seasoned meat products. Their sensor responses can reflect the comprehensive changes in saltiness, sourness, bitterness, and umami intensity and some flavor precursors. Haddi et al. used electronic sensing systems to evaluate the origin and storage time of red meat, indicating that odor and taste responses can provide complementary information for meat type identification and storage status analysis [164]. Related reviews also show that electronic noses are more commonly used for volatile odor identification, while electronic tongues can assist in the evaluation of adulteration, processing conditions, taste quality and shelf life [165].

Since electronic tongue sensors usually need to be in contact with liquid samples, intact meat samples generally cannot be used directly for measurement. Meat samples usually need to be minced or homogenized and extracted with water, buffer or other suitable solutions, and then the test solution is obtained by standing, centrifuging or filtering. The solid-to-liquid ratio, extraction time, extraction temperature, pH, dilution factor, and filtration method may change the composition of soluble flavor substances and the sensor response. During the measurement process, the measurement temperature, sensor soaking time, cleaning procedures, and sensor drift will also affect the results.

Electronic tongues can supplement meat taste and water-soluble component information, but their results cannot completely replace sensory evaluation, microbiological testing or physicochemical analysis. Lipid oxidation, protein hydrolysis, salt changes, and microbial metabolism also affect the smell, taste and texture of meat at the same time. It is difficult to fully explain complex quality changes by relying solely on liquid-phase sensing responses. The combination of electronic tongue and electronic nose, chromatographic analysis, spectral detection, and sensory evaluation can help improve the integrity of meat flavor and processing quality evaluation. Future research should further standardize sample extraction and sensor cleaning procedures, improve sensor stability, and strengthen the analysis of correlations between taste responses, sensory attributes, and physicochemical indicators.

#### 4.3. Volatile-Component and Odor-Fingerprint Analysis

Volatile organic compounds such as aldehydes, ketones, alcohols, esters, sulfur-containing compounds, and nitrogen-containing compounds are formed during meat storage, processing and microbial contamination [166–168]. Lipid oxidation, protein degradation, microbial activity, and thermal reactions collectively determine the volatile profile of meat, so these compounds can be used to explain flavor development and changes in spoilage odors and can serve as potential markers of freshness or contamination status [169].

Unlike electronic noses, which mainly obtain overall odor fingerprints, gas chromatography-mass spectrometry (GC-MS), gas chromatography-ion mobility spectrometry (GC-IMS), selected ion flow tube mass spectrometry (SIFT-MS) and headspace solid-phase microextraction-gas chromatography-mass spectrometry (HS-SPME-GC-MS) can identify specific volatile compounds and their changing patterns. These methods can provide a chemical basis for spoilage and flavor marker screening, electronic nose sensor selection, and odor response interpretation [170]. However, such methods often rely on headspace equilibration, extraction, chromatographic separation, or mass spectrometry, and their primary value lies in reference analysis, result confirmation, and mechanistic elucidation rather than direct non-destructive in-line screening.

Volatile component analysis has been used to monitor microbial contamination, evaluate storage conditions, compare packaging conditions, and differentiate meat cuts. In chicken, HS-SPME-GC-MS and HS-GC-IMS combined with OPLS-DA were used to identify volatile markers of early-stage contamination with *Staphylococcus aureus* [171]. A surface acoustic wave sensor that responds to aldehyde gases can monitor the odor changes of chicken during storage [172]. The former is able to identify specific volatiles and explain contamination-related metabolic processes, while the latter is closer to gas sensing methods suitable for on-site screening.

In pork, SIFT-MS can be used to monitor spoilage markers under different modified atmosphere packaging conditions. The results show that the O<sub>2</sub>/CO<sub>2</sub> ratio affects volatile components and their relationship with microbial growth and sensory rejection [173]. A multichannel spectral sensor combined with PLS-DA can distinguish fresh and spoiled pork, and the prediction-set accuracy reached 91.67% [174]. HS-SPME-GC-MS combined with multivariate analysis also identified characteristic metabolites formed during pork storage, providing a basis for explaining spoilage odors and screening sensing markers [161]. In addition, GC-IMS combined with chemometrics can be used to characterize the volatile components of different anatomical parts/cuts of donkey meat, among which ketones, alcohols, aldehydes, and esters are the main volatile categories and can be used as potential markers for part identification [175].

In general, electronic noses are suitable for obtaining overall odor fingerprints and performing rapid screening, electronic tongues mainly provide liquid-phase taste responses, and chromatography, mass spectrometry, and ion mobility spectrometry can identify specific volatiles and explain flavor or spoilage mechanisms. The information obtained by the three types of methods is complementary, but there are obvious differences in sample processing, instrument cost, analysis time, and suitability for field deployment. Volatile component analysis usually requires laboratory instrumentation and standardized sample processing, and its results are more suitable as a basis for sensor development, model interpretation, and confirmatory analysis. Future research should strengthen the development of volatile marker databases, standardized headspace sampling procedures, and portable gas sensing systems, and improve the reliability of odor and taste evaluation through verification across multiple batches and actual storage conditions.

Table 3 summarizes the representative applications of electronic noses and electronic tongues, and volatile component and odor fingerprint analysis in meat quality and safety evaluation.

**Table 3.** Representative applications of odor sensing, taste sensing, and volatile component analysis in meat quality and safety evaluation.

| Technology                            | Samples and Sample Size                                                                             | Target Variable/Application                                             | Sample Handling/Sampling Conditions                                                                                                                                                            | Sensor or Analytics Platform                                              | Method/Model                                                                        | Ref.  |
|---------------------------------------|-----------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------|
| gas sensor                            | Beef; sample size NR                                                                                | Freshness, color, and odor evaluation                                   | The gas released from the meat sample directly enters the detection system                                                                                                                     | NH <sub>3</sub> , H <sub>2</sub> S gas sensor                             | Sensor response and reaction kinetics analysis                                      | [176] |
| electronic nose                       | Pork; 50 meat samples                                                                               | Postmortem odor detection and quality evaluation                        | Collect volatile gases from meat samples; specific headspace conditions NR                                                                                                                     | Electronic nose sensor array                                              | Feature extraction, machine learning classification                                 | [177] |
| electronic nose                       | Beef; 35 meat samples                                                                               | Non-fresh beef identification                                           | Headspace equilibration at 60 °C, 500 rpm for 25 min                                                                                                                                           | Electronic nose sensor array                                              | SVM, SVR, RF                                                                        | [178] |
| electronic nose and electronic tongue | Beef patties; 780 patties in total; 12 samples, each used for electronic nose and electronic tongue | Beef heart blending ratio, smell, taste, and quality evaluation         | Electronic nose: collect headspace gas after incubation at 50 °C for 20 min; electronic tongue: measure water-soluble extracts                                                                 | Ultra-fast GC type electronic nose, $\alpha$ -Astree II electronic tongue | SAS 9.2 MIXED model, orthogonal comparison, and mean comparison without data fusion | [179] |
| electronic nose                       | Pork floss; 300 samples                                                                             | Source and authenticity assessment of meat floss                        | Place the floss in the sampling chamber at room temperature; delay 20 s, sample for 120 s, and then purge. HiSorb adsorption; thermal desorption analysis after incubation at 65 °C for 40 min | 8-sensor electronic nose array                                            | RF                                                                                  | [180] |
| electronic nose and volatile analysis | Chilled tan muton; 3 replicates per storage time point                                              | Identification and classification of volatile components during storage | Meat sample volatile gas enters the sensor detection chamber; specific equilibrium conditions NR                                                                                               | E-nose, HiSorb-TD-GC-MS                                                   | PLSR                                                                                | [181] |
| gas sensor                            | General meat sample; sample size NR                                                                 | Harmful gas and alcohol detection                                       | Meat sample volatile gas enters the sensor detection chamber; specific equilibrium conditions NR                                                                                               | MQ series gas sensors, micro-controllers                                  | Threshold and sensor response analysis                                              | [182] |
| electronic nose                       | Steak; 4 samples                                                                                    | Beef quality monitoring and spoilage detection                          | Store individually in 1.4 L airtight containers at 4 °C and 21 °C                                                                                                                              | IoT electronic nose system, gas sensor                                    | RF and IoT monitoring algorithm                                                     | [183] |
| electronic nose and volatile analysis | Beijing-You chicken; 3 of each variety                                                              | Quality evaluation and variety/adulteration identification              | Electronic nose: 5 g meat sample, 40 °C headspace, gas flow rate 3 L/min, sampling 60 s; GC-MS: 1 g meat sample, equilibration at 60 °C for 20                                                 | 16-sensor electronic nose, SPME-GC-MS                                     | PCA, LDA, and odor fingerprint analysis                                             | [184] |

|                          |                                                                                                                                                            |                                                                               |                                                                                                                                                                             |                                                                                 |                                                       |       |
|--------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|-------------------------------------------------------|-------|
|                          |                                                                                                                                                            |                                                                               | min, SPME extraction for 30 min                                                                                                                                             |                                                                                 |                                                       |       |
| electronic nose          | Chicken breast; 315 samples (105 samples for each of three packaging treatments); electronic nose analysis of two samples per treatment at each time point | Packaging conditions, storage quality, and volatile odor evaluation           | 2 g of meat sample was placed in a 20 mL headspace bottle and incubated at 50 °C and 500 rpm for 20 min                                                                     | Heracles Neo ultra-fast GC type electronic nose                                 | Peak area and volatility fingerprint analysis         | [185] |
| electronic nose          | Chicken and soy protein blend; 120 samples                                                                                                                 | Soy protein isolate adulteration identification                               | The ground chicken sample was sealed for 10 min to create headspace gas                                                                                                     | Portable electronic nose                                                        | SVM, SVR                                              | [186] |
| handheld electronic nose | Chicken thigh; 9 samples                                                                                                                                   | Real-time evaluation of poultry meat freshness                                | The equipment extracts headspace gas on the surface of the meat sample with a flow rate of 5.95 m <sup>3</sup> /h and a sampling period of 60 s                             | Cadaverine-responsive handheld electronic nose                                  | Sensor frequency response and freshness curve         | [187] |
| electronic nose          | Vacuum-packed chicken; sample size NR; 20 g per sample                                                                                                     | Freshness monitoring at room temperature and refrigerated conditions          | The meat sample was placed in a 100 mL beaker and sealed, and then measured after balancing for 30 min                                                                      | Electronic nose sensor array with reference to GC-MS and microbial detection    | SVR                                                   | [188] |
| electronic tongue        | Beef/pork and turkey/chicken blends; 18 samples per extraction method                                                                                      | Comparison of extraction methods and detection of low-level meat adulteration | Compare different meat sample extraction methods; the optimal dilution level of liquid meat extract is 1% (w/v), and cooking extraction has the best differentiation effect | Electronic tongue sensor array                                                  | LDA, PLS, PLSR                                        | [189] |
| electronic tongue        | 5 types of beef meat samples; 15 animals, 3 of each type                                                                                                   | Meat quality index correlation and variety classification                     | Obtain the extract after cooking the meat sample, dilute 50% to 100 mL with distilled water; sample for 120 s, clean for 20 s, and measure at room temperature              | $\alpha$ -Astree II potential electronic tongue                                 | PCA, LDA                                              | [190] |
| electronic tongue        | Beef; 5 samples                                                                                                                                            | Sous-vide beef umami evaluation                                               | Sous-vide cooking at 60 or 70 °C for 6 or 12 h; the control is cooking at 70 °C for 30 min; measure after                                                                   | Electronic tongue system, combined with nucleotide and free amino acid analysis | PCA, equivalent umami concentration (EUC) calculation | [191] |

|                                                     |                                                       |                                                                                      |                                                                                                                                                                                                            |                                                                    |                                                |       |
|-----------------------------------------------------|-------------------------------------------------------|--------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------|------------------------------------------------|-------|
| volatile component analysis                         | 3 pig breed/crossbred combinations; 34 meat samples   | Comparison of volatile components of different pig breeds                            | preparing the meat sample extract<br>The sample was placed in a headspace bottle, equilibrated at 55 °C for 15 min, and thermally desorbed at 230 °C after SPME extraction                                 | SPME-GC-MS                                                         | PCA, OPLS-DA and volatile fingerprint analysis | [192] |
| volatile component analysis                         | Beijing chicken; 38 samples                           | Evaluation of quality and volatile components at different storage temperatures      | HS-SPME extraction using 50/30 µm DVB/CAR/PDMS fiber                                                                                                                                                       | HS-SPME-GC-MS                                                      | Volatile components and multivariate analysis  | [193] |
| volatile components and processing quality analysis | Low-sodium marinated beef; 3 replicates per treatment | Effects of salt substitution on physicochemical quality, sensory and volatile flavor | Headspace samples were incubated at 80 °C and injected using a heated syringe                                                                                                                              | GC-IMS, combined with LF-NMR, sensory and physicochemical analysis | Fingerprints and multivariate analysis         | [194] |
| volatile component analysis                         | Goat meat; 2 replicates per storage condition         | Different freshness levels and volatile marker identification                        | Incubate at 60 °C for 15 min, shake at 500 rpm, and then inject headspace samples<br>Headspace samples were incubated at 60 °C for 15 min; automated headspace and SPME analyses were performed separately | GC-IMS                                                             | PCA, volatile fingerprint analysis             | [195] |
| volatile component analysis                         | Daokou roast chicken; 3 replicates per treatment      | Comprehensive characterization of taste and aroma characteristics                    |                                                                                                                                                                                                            | HS-GC-IMS, HS-SPME-GC-MS                                           | PCA, PLSR and chemometric analysis             | [196] |

Abbreviations: NR, not reported; NH<sub>3</sub>, ammonia; H<sub>2</sub>S, hydrogen sulfide; SVM, support vector machine; SVR, support vector regression; RF, random forest; GC, gas chromatography; SAS, Statistical Analysis System; TD-GC-MS, thermal desorption–gas chromatography–mass spectrometry; PLSR, partial least squares regression; IoT, Internet of Things; SPME, solid-phase microextraction; PCA, principal component analysis; LDA, linear discriminant analysis; PLS, partial least squares; EUC, equivalent umami concentration; OPLS-DA, orthogonal partial least squares discriminant analysis; HS-SPME, headspace solid-phase microextraction; DVB/CAR/PDMS, divinylbenzene/carboxen/polydimethylsiloxane; GC-IMS, gas chromatography–ion mobility spectrometry; LF-NMR, low-field nuclear magnetic resonance.

## 5. Other Non-Destructive Detection Technologies

In addition to spectroscopy, imaging, and odor sensing technologies, ultrasound, microwave sensing, impedance, and dielectric property measurements, as well as low-field nuclear magnetic resonance are also used for meat quality assessment. These techniques obtain information such as acoustic wave propagation, electromagnetic response, ion migration, and water relaxation, respectively, and can be used to characterize tissue structure, cell integrity, water status, and changes that occur during processing. Therefore, they have certain advantages for assessing freeze–thaw damage, water-holding capacity, moisture migration, tissue integrity, and process monitoring and can provide supplementary information for optical detection [197].

### 5.1. Ultrasonic Detection

Ultrasonic testing obtains information related to the composition and internal structure of meat by analyzing the propagation velocity, attenuation, reflection, and scattering of sound waves in meat tissue. The moisture and fat content, muscle fiber arrangement, cell integrity, and protein status in meat all affect acoustic impedance and sound wave propagation. Therefore, ultrasonic parameters can be used to characterize tenderness, freeze–thaw status, moisture migration, and processing quality changes [198]. Compared with optical methods that mainly obtain surface or near-surface information from meat samples, ultrasound is more sensitive to changes in the internal structure of tissues and can complement information obtained by spectroscopy and machine vision in internal quality evaluation.

Low-intensity ultrasound mainly evaluates the status of meat by collecting acoustic parameters. Studies have used ultrasonic pulse speeds and attenuation parameters at different frequencies to analyze sirloin quality. The results show that the acoustic response can reflect changes in tissue status and some quality indicators [199]. During monitoring of the freezing and thawing process, the melting of ice crystals, redistribution of water, and structural changes in muscle tissue will affect the propagation characteristics of sound waves. Therefore, ultrasonic signals can be used to determine the degree of thawing and the endpoint of beef thawing [200]. This type of method offers rapid measurement and minimal sample preparation and the ability to reflect internal structural changes, but the relationship between acoustic parameters and specific quality attributes still needs to be determined in conjunction with reference measurements such as texture, juice loss, temperature, and microstructure.

In addition to its use in quality inspection, ultrasonic energy is also used to regulate meat processing. High-intensity ultrasound can affect muscle fiber structure, protein properties and mass transfer through cavitation, mechanical vibration and micro-jet, thereby affecting thawing, drying, marination/curing, tumbling, and other low-temperature processes. The combination of contact ultrasound and infrared radiation can promote moisture migration of air-dried beef, improve drying efficiency and affect product quality [201]. Ultrasound-assisted L-lysine treatment can change the pH, texture, water-holding capacity and myofibrillar protein properties of pork during postmortem maturation [202]. In frozen meat processing, single-frequency ultrasound can shorten the thawing time of frozen goose meat and affect thawing loss, meat quality, and microstructure [203]. Ultrasound-assisted intermittent tumbling and marinating can also improve processing efficiency and affect final product quality by promoting mass transfer and changing muscle fiber structure [204–208].

The use of ultrasound in low-temperature meat processing further demonstrates that processing frequency, power, and time collectively affect protein structure, moisture migration and tissue integrity [209]. These changes not only determine the actual effect of ultrasound-assisted processing, but also provide a quality basis for using acoustic parameters to monitor the processing operation. Together, these studies position ultrasound as both a sensing modality for characterizing sample status and a processing tool whose acoustic and quality responses can support process monitoring.

Ultrasonic measurement is easily affected by factors such as meat sample thickness, fat distribution, muscle fiber direction, probe position, coupling medium, sample temperature, and detection frequency. Although contact measurements do not significantly damage the sample, differences in probe pressure and coupling status may reduce the reproducibility of the results. The acoustic parameters, sample morphology and reference indicators used in different studies have not yet been unified, and the transferability of models across different meat species, cuts, and processing conditions still needs to be further verified. Future research should strengthen the standardization of probe layout, coupling

conditions, and acoustic parameters and carry out performance evaluation across multiple batches, different cuts, and actual processing environments to improve the reliability of ultrasonic testing in meat quality evaluation and process monitoring [210].

### 5.2. Microwave, Impedance, and Dielectric Property Detection

Microwave sensing, impedance spectroscopy, and dielectric property measurements all exploit the response of meat tissue to electric or electromagnetic fields to obtain quality information. Moisture status, ion concentration, cell membrane integrity, fat content, and tissue structure in meat affect conductivity, impedance, dielectric constant, and dielectric loss. Cell damage, water redistribution, ion migration and protein changes that occur during storage, spoilage, freezing, thawing, and processing may cause changes in electrical and dielectric parameters, so these methods can be used to evaluate freshness, freeze-thaw damage, compositional characteristics and processing status [211–214].

Impedance detection usually applies alternating-current (AC) signals to the meat sample through electrodes and measures the impedance amplitude and phase changes at different frequencies. Relevant reviews show that bioelectrical impedance has been used to evaluate indicators such as intramuscular fat, water, TVB-N, pH, shear force, and freshness, and has the characteristics of fast response, relatively simple equipment structure, and easy miniaturization [215]. Compared with surface images or single spectral responses, impedance measurement can provide information related to cell integrity and water and ion migration, but it is not a direct measurement of a specific quality indicator, and its application usually relies on empirical models established between impedance characteristics and traditional reference values.

In freezing and thawing identification, Dell'Osa et al. developed a portable electrical impedance spectroscopy device and found that the impedance per unit length of frozen and thawed beef was lower than that of unfrozen beef, indicating that electrical changes caused by cell structure damage and juice migration can be used to identify undeclared freezing and thawing treatments [216]. The impedance method has also been used to evaluate the quality changes of camel meat under repeated freezing and thawing conditions, and to analyze its relationship with indicators such as pH and color [217]. In freshness evaluation, electrical impedance spectroscopy can be used to monitor electrical changes associated with transport and storage duration [218] and can also be combined with image classification to build a low-cost beef freshness evaluation system [219].

In terms of composition and authenticity evaluation, bioelectrical impedance can be used to predict intramuscular fat and some physicochemical properties of bovine longissimus dorsi muscle [220]. Impedance spectroscopy combined with machine learning is also used to identify beef adulteration and low-quality meat [221]. In addition, related methods have been used to evaluate the meat content and internal foreign matter in beef balls [222]. These studies show that electrical characteristics can support a variety of quality assessment tasks, but model performance may be affected by sample morphology, degree of compaction, electrode position and contact status. Models established for intact muscles may not be directly applicable to minced meat or processed meat products.

The dielectric properties reflect the polarization and energy loss behavior of meat samples in alternating electromagnetic fields, and their responses are related to free water, bound water, ion migration, and tissue structure. Radiofrequency and microwave band dielectric parameters of chicken meat at 5–146 h postmortem have been used to analyze protein-related changes, pH, meat color, lactic acid, and microstructure, indicating that dielectric properties and ionic conductivity have the potential to estimate postmortem time [223]. Compared with contact impedance measurement, microwave and dielectric sensing can achieve non-contact or weak contact measurement under certain conditions, but the results are more sensitive to frequency, temperature, sample thickness and geometry.

Microwaves are currently mainly used for heating and drying processing of meat and other animal-derived muscle foods. Microwave treatment causes moisture migration, temperature changes and structural changes within the sample, and further affects texture, protein oxidation and flavor formation. Zhang et al. studied the quality changes of *Macrobrachium rosenbergii* meat at different stages of microwave-vacuum drying through drying kinetics, moisture status and distribution, physicochemical properties, microstructure, myofibrillar protein oxidation and volatile component analysis, and determined the relationship between moisture status transformation and quality deterioration [101]. These relationships provide a basis for selecting dielectric, moisture state, and structural indicators for non-destructive monitoring and for developing online quality monitoring methods during microwave processing.

Overall, microwave sensing, impedance spectroscopy, and dielectric detection can provide complementary information about cell integrity, water status, ion migration, and tissue structure. Their measurements are easily affected by factors such as electrode contact, surface moisture, sample temperature, muscle fiber direction, sample thickness, and frequency range. Future research should unify sample size, electrode arrangement, and temperature control methods, clarify the mechanism between different frequency responses and quality changes, and carry out model verification across meat types, equipment, and actual production environments. Portable impedance devices and non-contact microwave sensors have potential for field application, but their cost-effectiveness and suitability for online deployment still need to be evaluated together with detection throughput, calibration maintenance, and production conditions.

### 5.3. Low-Field Nuclear Magnetic Resonance

Low-field nuclear magnetic resonance (LF-NMR) measures the relaxation behavior of hydrogen protons to characterize the status and mobility of water and fat and their interactions with the meat matrix [224]. In the transverse relaxation time ( $T_2$ ) distribution, the component with the shortest relaxation time is usually related to water tightly bound to macromolecules such as proteins, the medium relaxation time component mainly corresponds to the immobilized water located in the myofibril network, and the component with longer relaxation time usually reflects free water with higher mobility in the inter-myofibrillar or extracellular spaces. The specific  $T_2$  ranges of different components will vary with meat type, instrument parameters, and measurement conditions, so it is not appropriate to use a universal time range or threshold to interpret all meat samples.

In the  $T_2$  relaxation distribution of meat, immobile water is usually the main moisture component, and its signal ratio and relaxation characteristics can reflect the degree of water binding by the myofibrillar protein network. During storage, freezing and thawing, curing or marination, drying and heating, protein denaturation, muscle fiber contraction, and cell membrane damage will cause part of the immobilized water to become more mobile and move to the extracellular space. Therefore, an increase in the proportion of long  $T_2$  components or a shift of the moisture peak toward longer relaxation times generally indicates enhanced moisture mobility and may be accompanied by increased juice loss and decreased water-holding capacity. When water becomes more constrained by the protein network, its relaxation time may be shortened. The above changes still need to be explained in conjunction with reference indicators such as juice loss, centrifugal loss, cooking loss, and microstructure.

Compared with oven drying and Soxhlet extraction for moisture/fat determination and centrifugation-based tests of water-holding capacity, LF-NMR requires less sample processing and can obtain moisture- and fat-related signals without chemical extraction. Tang et al. used the CPMG sequence to obtain pork  $T_2$  distributions and combined it with a chemometric model to simultaneously predict fat and moisture content [225]. In

addition to composition prediction, LF-NMR can be used to analyze tissue damage caused by ice crystals during freezing and thawing, water migration during drying and curing, and protein shrinkage and water release caused by heating, helping to explain water-holding capacity, juice loss, and textural changes [226].

The advantage of LF-NMR is that it can distinguish moisture in different migration states and provide mechanistic information on moisture changes in meat; however, the  $T_2$  signal is not directly equivalent to water-holding capacity, tenderness or freeze–thaw damage. Peak position and peak area are also affected by sample temperature, instrument parameters, sample size, fat signal overlap, and data fitting methods, so they need to be combined with traditional physicochemical measurements and validation using independent samples. The purchase and maintenance cost of LF-NMR equipment is also higher than that of portable spectroscopy, machine vision, and impedance equipment, limiting its direct application in conventional production lines.

In general, LF-NMR is mainly suitable for laboratory evaluation of moisture status, water-holding capacity, freeze–thaw damage and processing changes, but has limited ability to directly characterize meat color, odor, microorganisms, or specific adulterants. Future research should unify relaxation parameters and peak component interpretation methods, strengthen the validation of the relationships between  $T_2$  distributions and drip loss, texture, and microstructure, and explore complementary applications of low-field NMR and spectral imaging, electrical detection, and other sensing information. Ultra-sound, impedance and dielectric detection, and LF-NMR provide information on tissue structure, moisture and ion migration, and relaxation behavior, respectively, providing an information basis that is different from optical and odor sensing for subsequent multi-source information fusion and comprehensive meat quality evaluation.

## 6. Multi-Source Information Fusion and Intelligent Evaluation

Changes in meat quality involve multiple processes such as chemical composition, color and texture, tissue structure, moisture migration, lipid oxidation, microbial metabolism, and formation of volatile components. The information obtained by different detection technologies captures different types of information: spectral methods mainly reflect chemical composition and molecular structure, imaging technologies can provide color, texture, and spatial distribution information, while electronic noses and colorimetric sensor arrays mainly respond to volatile components [227–229]. Electrical detection and low-field NMR can provide information about ion migration, cell integrity, and water status, respectively [230–232]. A single detection technology can usually reflect only a certain part of the changes in meat quality. Joint analysis of information from different sources can help evaluate meat freshness, lipid oxidation, microbial contamination, freeze–thaw status and authenticity from multiple angles [14].

### 6.1. From Multi-Response Sensing to Multi-Source Information Fusion

Information integration in intelligent meat evaluation begins with multi-response perception within a single sensing platform. Electronic noses, electronic tongues and colorimetric sensor arrays usually contain multiple cross-reactive sensing units. Different sensing units respond to mixed gases, soluble taste substances or volatile components to varying degrees, thereby forming fingerprint information that can characterize the overall state of the sample. For example, colorimetric sensor arrays can monitor pork and chicken freshness using a variety of chemically responsive dyes [233,234], whereas a bionic taste sensor can identify the adulteration of beef with other meats through multiple taste response channels [235]. This type of method increases the information dimensionality of a single sensing platform, but these responses still come from the same sensing principle, so it is called array-based multi-response sensing rather than multi-source fusion.

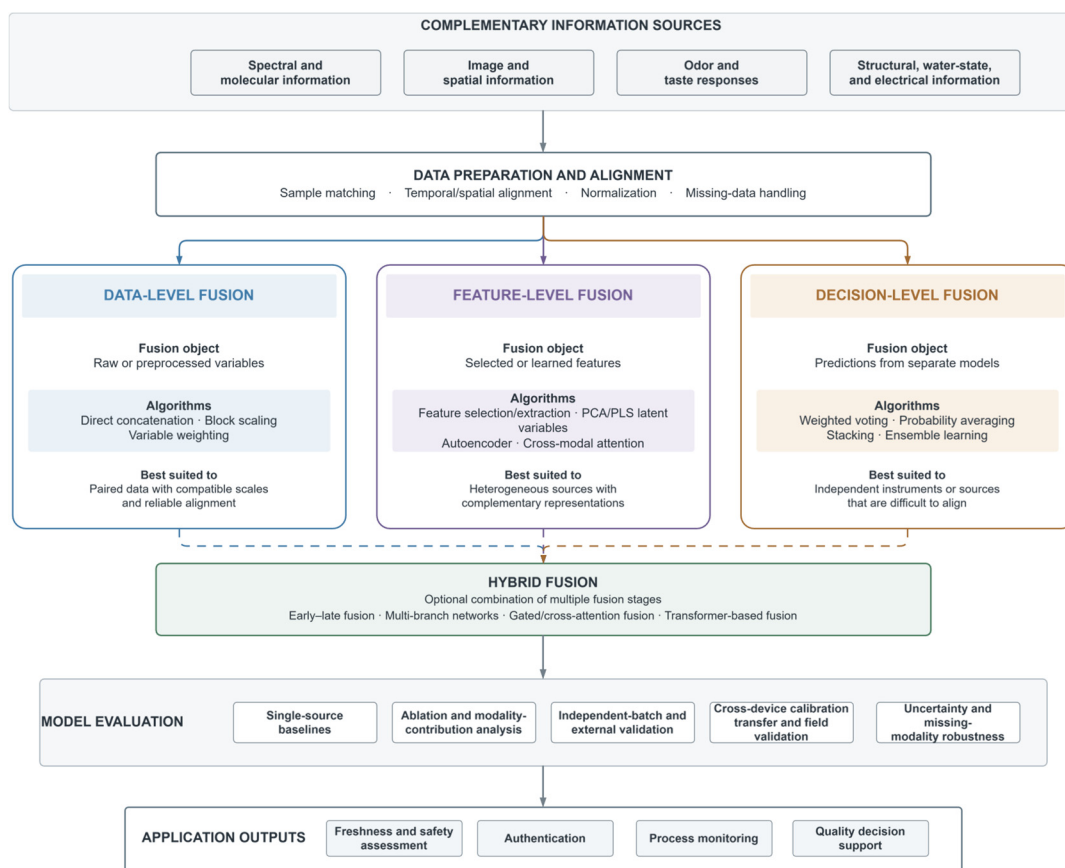
With the development of chemometrics and machine learning, researchers have begun to extract spectra, colors, textures or derived representations from the same information source, and improve data utilization efficiency through multi-branch networks or feature combinations. The dual-branch hierarchical feature network based on HSI can extract spectral features at different levels at the same time for classifying the freshness of chilled mutton [236]. Machine vision research can combine color, texture and morphological parameters for chicken freshness evaluation [237]. A two-dimensional correlation spectral representation and a three-dimensional convolutional neural network were also used to mine changes related to pork lipid oxidation in HSI data [238]. Although these methods achieve joint modeling of multiple features from the same source, they do not add new sources of sensing information. Their performance improvements mainly come from further utilization of the internal structure of the original data.

The combined application of different detection technologies on the same sample further expands the scope of meat quality characterization. Tian et al. used HSI, confocal laser scanning microscopy and GC-IMS to study changes in moisture status and lipid oxidation, microstructure, and volatile profiles in dry-cured pork, respectively, to explain the quality development during processing from multiple levels [239]. This multi-technique joint characterization can reveal the connection between different quality changes, but various types of data can still be analyzed separately and are not entered into the same prediction model [240–244].

When data from different devices or sensing principles are combined in a unified model, information integration extends to true multi-source information fusion. Existing research has combined an electronic nose with multispectral imaging [14], FTIR and MSI [245], NIR and Raman spectroscopy [246], NIR and colorimetric sensor arrays [247], HSI with an electronic nose [248], and fluorescence HSI with an electronic nose [249]. Complementarity between different information sources forms the basis for integration. For example, NIR spectroscopy and HSI mainly reflect meat composition and optical changes, electronic noses and colorimetric arrays provide volatile odor responses, machine vision and image texture describe surface appearance and texture, and tactile sensing can supplement information related to elasticity and tissue status [250–252]. Therefore, the value of multi-source fusion is not to simply increase the number of variables, but to utilize the differentiated responses of different sensing methods to the same quality change.

## 6.2. Applications of Fusion Strategies at Different Levels

Multi-source information can be combined at different stages such as raw data, features, or model outputs, thus forming data-level, feature-level, and decision-level fusion. The choice of fusion stage is closely related to the data type. Data from similar sources, consistent dimensions and acquisition protocols can be combined directly after preprocessing, while spectral, image and odor data with large differences in dimensionality are usually first extracted separately and then jointly modeled. When different sensors are processed relatively independently, the model outputs can also be combined after each has completed predictions. Figure 2 summarizes the overall framework for multi-source information fusion, from data preparation and alignment, fusion level selection to model evaluation and application output, and lists commonly used algorithms at different fusion levels and their applicable conditions.



**Figure 2.** Algorithmic framework and validation pathway for multi-source information fusion in meat quality assessment.

Data-level fusion retains relatively complete original information from different information sources, and is suitable for detection technologies with similar spectral ranges or relatively consistent data structures. Robert et al. used low-level fusion of Raman and FTIR data to predict red meat pH and intramuscular fat content [253]. The two techniques capture complementary molecular vibrational information, and their direct combination expands the coverage of meat composition and structural information. In this study, low-level fusion showed good results for intramuscular fat prediction, but the direct combination of a large number of variables also increased data redundancy and computational burden.

Data from two hyperspectral systems can also be fused at a lower level. Cai et al. used visible–near-infrared and near-infrared HSI data to predict chicken breast TVB-N and total viable count (TVC), and improved the ability to comprehensively characterize color, composition, and spoilage changes by fusing information from different bands [254]. Chung and Yoon combined VNIR and SWIR hyperspectral data to detect foreign matter on the surface of chicken breast [255]. These datasets have similar spatial–spectral structures, which facilitates band matching and joint modeling, but spatial registration and band overlap between devices will still affect the fusion results.

Feature-level fusion is widely used in meat research. This method extracts key variables separately from each sensing modality and then combines them for modeling. Li et al. combined protein structural information provided by Raman spectroscopy with textural features of minced meat gel images to predict gel strength and water-holding capacity [256]. Nunekpeku et al. fused NIR and Raman spectral features to predict the gel strength of ultrasound-treated chicken mince. The results showed that the fusion model can simultaneously utilize the complementary responses of the two spectral modalities in composition and molecular structure [246].

Feature-level fusion of optical information and odor response enables the evaluation of meat freshness in terms of compositional and volatile changes. Wei et al. combined NIR characteristics with colorimetric sensor array responses to predict TVB-N changes in pork during storage [247]. Feng et al. integrated NIR and paper-based chromogenic array data to monitor lipid oxidation and changes in volatile components of ground beef [257]. Compared with simply adding similar spectral variables, this type of combination introduces information from different sensing mechanisms, but the differences in dimensionality and response scales between the two types of data also increase the complexity of feature screening.

Decision-level fusion builds a separate model for each information source, and then combines the prediction results of different models. Cheng et al. used HSI to obtain spectral, color, and texture information of frozen and thawed pork, and used an electronic nose to obtain odor responses, and compared the predictive performance of pixel-level, feature-level, and decision-level fusion for predicting moisture content [248]. The improved decision fusion achieved better prediction performance, which shows that when the structures of spectral-image data and odor data are quite different, the combination of model outputs can reduce the dimensional imbalance caused by direct splicing of the original data.

Different levels of fusion have different applicability to specific quality indicators. In the study by Robert et al., high-level fusion performed best in predicting red meat pH, while low-level fusion was more advantageous in predicting intramuscular fat [253]. This difference shows that the benefits of fusion depend not only on the algorithm used but also on how the target attributes are reflected in different sensing modalities. pH changes may affect the prediction results of multiple spectral systems at the same time, which is suitable for comprehensive judgment in the model output stage; intramuscular fat produces a strong spectral signature, and the combination of original or preprocessed spectra can retain more composition information.

In recent years, deep learning has further expanded the connections between different levels of fusion. Cheng et al. introduced fluorescence HSI and electronic nose data into a hybrid fusion attention network, combining early feature interaction with late information integration in a parallel architecture for pork TVB-N prediction [249]. Gu et al. combined the volatile organic compound information obtained by SERS gas sensing with the moisture distribution information obtained by LF-NMR to establish a beef freshness prediction platform [258]. These studies link volatile-response information to internal moisture or composition changes, expanding the meat quality information covered by multi-source fusion.

### *6.3. Performance and Applicability of Multi-Source Fusion*

The application of multi-source fusion is most concentrated in the evaluation of meat freshness. Microbial growth, protein degradation, color changes, and volatile metabolite formation that occur during putrefaction cause spectral, image, and odor response changes, respectively. Spyrelli et al. combined FTIR, MSI, and an electronic nose to analyze the microbial spoilage and quality changes of marinated chicken. Different sensing information described the storage process in terms of composition, surface optical characteristics, and volatile odor [251]. The fusion of electronic nose, machine vision and tactile sensing has also been used to evaluate the freshness of pork and chicken, providing information on odor, color, and surface elasticity, respectively [252].

The information expansion brought by fusion does not necessarily translate into the same degree of performance improvement in all detection tasks. Heffer et al. compared the predictive performance of FTIR, MSI and their fusion models on microbial spoilage of chicken and beef [245]. The fusion model reduced prediction errors under most storage

conditions and showed better stability across batches; however, in some scenarios, MSI alone achieved results comparable to those of the fusion model. When a certain sensor can already fully reflect target changes, new information sources may contribute limited additional information.

The connection between target indicators and sensing information determines the actual value of fusion. For freshness and microbial spoilage, compositional, color, and volatile profiles change simultaneously, and spectroscopy, imaging, and odor sensing are obviously complementary. For indicators with relatively concentrated responses, such as moisture content, intramuscular fat, or meat color, a single spectroscopic or imaging system can sometimes achieve better results. The advantage of fusion models in these tasks depends more on the quality of single-source data, sample range, and detection environment than on the number of information sources per se.

The acquisition protocols of different information sources will also affect the fusion results. Spectra and images can be collected from the surface of meat samples in a shorter time, while electronic noses usually require headspace equilibration, electronic tongues require preparation of liquid extracts, and LF-NMR has independent measurement conditions. Different collection times and sample states may cause each information source to reflect different stages of meat changes. Existing laboratory research usually uses fixed sample identifiers and unified processing conditions to ensure sample matching across modalities. However, in continuous processing and production line environments, sample positioning, acquisition synchronization, and equipment speed still affect the matching between multi-source information.

Differences in data dimensions and variable distributions are another influencing factor in fusion modeling. When high-dimensional spectral or image features are directly combined with a small number of odor sensor responses, the model may be biased toward information sources with a larger number of variables. Feature selection, normalization, and dimensionality reduction can attenuate this difference, but may also remove variables of complementary significance. Deep fusion models can automatically extract high-level features from different data, but their parameter count and sample requirements are usually higher than traditional chemometric models.

At present, most meat fusion research is still based on specific meat types, storage conditions and experimental equipment, and model performance is mainly evaluated through random partitioning or internal test sets. Some studies have begun to use independent batches, nested cross-validation or single-source baselines to analyze the benefits of fusion [245]. As sample sources and testing environments expand, distribution shifts caused by different batches, equipment, and production conditions will further affect the stability of the fusion model. Therefore, the application value of multi-source fusion is reflected not only in model accuracy but also in whether the performance gains can be maintained when sample and measurement conditions change.

#### *6.4. Applicability Conditions and Practical Limitations of Multi-Source Fusion*

Multi-source fusion is more suitable for composite quality tasks that cannot be adequately characterized by a single sensor. For example, meat spoilage involves microbial growth, composition changes, surface color changes, and volatile metabolite formation. Combining spectral or image information with odor sensing information can reflect this process from different levels. Similarly, spectra and images can be used to characterize meat composition and spatial distribution, with LF-NMR and electrical detection complementing information on moisture status, cell integrity, and ion migration. For authenticity assessment, freeze-thaw monitoring, and processing quality evaluation, whether fusion is necessary depends on whether the target attributes can be stably identified through a single information source.

When a single sensor can already meet the accuracy, detection speed, and application cost requirements, a complex fusion system may not be a more reasonable choice. Adding sensors will bring equipment purchase, maintenance, calibration, acquisition synchronization, and data processing costs, and may reduce online detection throughput. The aging speed and environmental sensitivity of different devices are also inconsistent, and drift in any one sensor may affect the fusion model output. Therefore, the choice of fusion strategy should not only consider the prediction performance but also compare the information gain, model complexity, detection time, operating costs, and maintenance requirements.

Existing meat multi-source fusion research mainly focuses on feature-level fusion under laboratory conditions, with relatively few studies of data-level and decision-level fusion. Most models are based on specific meat species, cuts, storage conditions, and instruments, and their applicability across meat species, cuts, equipment, and production environments still lacks sufficient verification. Future research should strengthen sensing data collection and alignment standards, establish shared datasets containing multiple batches, different origins, and different processing conditions, and carry out cross-device calibration transfer, external validation, and uncertainty evaluation. On this basis, lightweight models, interpretable fusion, sensor contribution analysis and modular equipment design will help determine the actual value of different information sources and promote the development of multi-source fusion from laboratory models to quality screening and decision support in the production process.

Table 4 summarizes representative studies according to eight categories: array-based multi-response sensing, single-source multi-feature modeling, multi-technique joint characterization, data-level fusion, feature-level fusion, decision-level fusion, multi-level fusion comparison, and hybrid fusion. This framework characterizes the progression of information utilization in intelligent meat assessment from multidimensional responses within a single platform to coordinated integration across sensing modalities and modeling levels, while distinguishing feature expansion within a single information source, parallel characterization by multiple technologies, and cross-source information fusion within a unified model.

**Table 4.** Representative applications of multi-response sensing, multi-feature modeling and multi-source information fusion in meat quality evaluation.

| Information Integration Type       | Information Source/Technology Combination | Samples and Sample Size                         | Main Input Information                                                        | Target Variable/Application                                | Fusion Strategies and Models                                       | Ref.  |
|------------------------------------|-------------------------------------------|-------------------------------------------------|-------------------------------------------------------------------------------|------------------------------------------------------------|--------------------------------------------------------------------|-------|
| Array-based multi-response sensing | Colorimetric sensor array                 | Pork; sample size NR                            | Color response produced by multiple porphyrins and pH indicators<br>RGB color | Real-time monitoring of freshness                          | Array response characteristics combined with multivariate analysis | [233] |
| Array-based multi-response sensing | Colorimetric sensor array                 | Chicken; 80 modeling samples                    | changes of various chemically responsive dyes                                 | TVB-N and freshness prediction                             | CARS, PLS, SVM, and other algorithms                               | [234] |
| Array-based multi-response sensing | Bionic electronic tongue                  | Adulterated samples of beef, chicken, duck, and | Response of multiple taste sensing units to water-soluble ingredients         | Meat adulteration identification and proportion prediction | Fisher LDA, ELM, PLS                                               | [235] |

|                                        |                                                           |                                                                             |                                                                                     |                                                                  |                                                                                          |
|----------------------------------------|-----------------------------------------------------------|-----------------------------------------------------------------------------|-------------------------------------------------------------------------------------|------------------------------------------------------------------|------------------------------------------------------------------------------------------|
|                                        |                                                           | pork; 228 samples                                                           |                                                                                     |                                                                  |                                                                                          |
| Single-source multi-feature modeling   | HSI multi-layer spectral characteristics                  | Chilled fresh mutton; 210 meat samples, forming 4200 ROI spectra            | Local and hierarchical spectral features in the same HSI data                       | Freshness level identification                                   | Dual-branch hierarchical spectral feature sensing network (DBHSNet) [236]                |
| Single-source multi-feature modeling   | RGB machine vision                                        | Chicken breast; sample size NR                                              | Color, texture, and morphological features in the same image                        | Freshness classification                                         | Multi-feature combination; PCA, SVM, RF, GBDT, NBC [237]                                 |
| Single-source multi-feature modeling   | HSI + two-dimensional correlation spectral representation | Pork; sample size NR                                                        | Raw spectra, 2D correlation features, and spatial information in the same HSI data  | Lipid oxidation assessment                                       | Generalized/asynchronous 2D correlation analysis, PLSR, 3D-CNN [238]                     |
| Single-source multi-feature modeling   | NIR + multiple physicochemical indicators                 | Modified atmosphere-packaged mutton; 180 meat samples, 900 spectra obtained | NIR characteristics and indicator information such as pH, meat color, and TVB-N     | Comprehensive freshness evaluation                               | Multi-index statistical fusion; PLSR, SVM [259]                                          |
| Single-source multi-feature modeling   | FT-NIR                                                    | Pork; 402 samples, including 270 training sets and 132 test sets            | Preprocessed FT-NIR spectral characteristics                                        | Storage time identification                                      | FCM, KHM and GK fuzzy clustering [260]                                                   |
| Single-source multi-feature modeling   | NIR                                                       | Ultrasonicated chicken mince; 120 samples                                   | NIR spectrum and filtered informative wavelengths                                   | Gel strength prediction                                          | SVM, ELM and variable selection algorithms [261]                                         |
| Multi-technique joint characterization | HSI + CLSM + GC-IMS                                       | Dry-cured pork; 126 samples                                                 | Water and lipid oxidation related spectra, micro-structure, and volatile components | Moisture, TBARS, structure, and flavor changes during processing | HSI-PLSR and informative-wavelength selection; CLSM and GC-IMS analyzed separately [239] |
| Feature-level fusion                   | Raman spectrum + image texture                            | Ultrasonicated minced pork; 120 samples                                     | Raman molecular structure information + GLCM surface texture characteristics        | Gel strength and water-holding capacity prediction               | Complete feature splicing; ELM, SVM, CNN [256]                                           |
| Feature-level fusion                   | NIR + Raman spectroscopy                                  | Ultrasonicated chicken mince; 120 samples                                   | NIR composition response + Raman molecular vibration information                    | Gel strength prediction                                          | Spectral data fusion; CNN, LSTM [246]                                                    |

|                               |                                                    |                                                                                         |                                                                                                                                    |                                                                  |                                                                     |       |
|-------------------------------|----------------------------------------------------|-----------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------|---------------------------------------------------------------------|-------|
| Multi-level fusion comparison | Raman + FTIR                                       | Venison, lamb, and beef; 90 samples in total                                            | Raman and FTIR molecular vibration characteristics<br>Visible color response + composition information in two near-infrared ranges | pH and intramuscular fat prediction                              | Low-level, mid-level, and high-level fusion; PLS                    | [253] |
| Multi-level fusion comparison | VNIR-HSI + NIR-HSI                                 | Chicken breast; 240 samples                                                             | VNIR color and near-infrared information + SWIR spectrum information                                                               | Simultaneous prediction of TVB-N and TVC                         | Low-level and mid-level fusion; deep learning fusion network        | [254] |
| Data-level fusion             | VNIR-HSI + SWIR-HSI                                | Chicken breast and surface foreign matter; sample size NR                               | Chemical composition information + surface optical characteristics + volatile odor response                                        | Surface foreign body identification                              | Dual hyperspectral data fusion; RF                                  | [255] |
| Feature-level fusion          | FTIR + MSI + electronic nose                       | Marinated chicken; 209 samples, plus 40 independent test samples                        | Molecular spectral information + color, spatial, and fluorescence response                                                         | Microbial spoilage and freshness classification                  | Two-source or three-source feature combination; PLSR, SVR, LDA, SVM | [251] |
| Multi-level fusion comparison | FTIR + MSI/fluorescence MSI                        | Chicken and beef spoilage dataset; sample size varies with batch and storage conditions | Volatile odor response + multispectral color and spatial information                                                               | Prediction of microbial spoilage degree                          | Feature-level fusion, decision-level fusion, and stacking modeling  | [245] |
| Decision-level fusion         | Electronic nose + MSI                              | Beef; MSI used 84 samples, and the electronic nose used 58 samples                      | Surface color and texture + H <sub>2</sub> S and NH <sub>3</sub> gas response                                                      | Prediction of TVC, aerobic plate count (APC), and spoilage level | Single source model output combination; neuro-fuzzy regression      | [14]  |
| Feature-level fusion          | Visible light image + gas sensor                   | Beef; sample size NR                                                                    | Odor parameters + color parameters + surface elasticity and tactile parameters                                                     | Real-time freshness classification                               | YOLOv11, ViT-CNN, RF, and multi-modal feature fusion                | [250] |
| Feature-level fusion          | Electronic nose + machine vision + tactile sensing | Pork and chicken; 28 samples of each meat type                                          | Composition-related NIR information + color response caused by                                                                     | Freshness and storage time evaluation                            | Multi-source feature splicing; PCA, SVM, PLS                        | [252] |
| Feature-level fusion          | NIR + paper-based chromogenic array                | Ground beef; sample size NR                                                             | TBARS and lipid oxidation monitoring                                                                                               | NIR and chromogenic-array feature fusion; PLSR, eNet, RF, SVR    |                                                                     | [257] |

|                               |                                   |                                                                          |                                                                                                          |                                                 |                                                                             |       |
|-------------------------------|-----------------------------------|--------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|-------------------------------------------------|-----------------------------------------------------------------------------|-------|
| Feature-level fusion          | NIR + colorimetric sensor array   | Pork; 108 samples collected; 104 used for modeling                       | volatile organic compounds<br>NIR composition information + color response caused by volatile components | TVB-N and freshness prediction                  | Feature fusion and variable screening; Si-CARS-PLS                          | [247] |
| Multi-level fusion comparison | HSI + electronic nose             | Pork with different freeze–thaw cycles; 240 samples                      | Spectral, color, and texture information + volatile odor response<br>Fluorescence                        | Moisture content prediction                     | Pixel-level, feature-level, traditional, and improved decision fusion; PLSR | [248] |
| Hybrid fusion                 | Fluorescent HSI + electronic nose | Pork; 400 samples, with 80 samples at each storage stage                 | spectrum and spatial characteristics + electronic nose time series response<br>SERS response             | TVB-N and freshness prediction                  | Early-late hybrid fusion, attention mechanism; HFA-Net                      | [249] |
| Hybrid fusion                 | SERS gas sensing + LF-NMR         | Beef; sample size NR; 1020 sets of spectral and relaxation data obtained | of volatile amines + internal moisture relaxation and distribution information                           | Evaluation of beef freshness and storage status | Dynamic deep fusion; EfficientNetB0, MobileViT                              | [258] |

Abbreviations: NR, not reported; RGB, red, green, and blue; TVB-N, total volatile basic nitrogen; CARS, competitive adaptive reweighted sampling; PLS, partial least squares; SVM, support vector machine; LDA, linear discriminant analysis; ELM, extreme learning machine; HSI, hyperspectral imaging; ROI, region of interest; DBHSNet, dual-branch hierarchical spectral feature sensing network; PCA, principal component analysis; RF, random forest; GBDT, gradient boosting decision tree; NBC, naive Bayes classifier; PLSR, partial least squares regression; CNN, convolutional neural network; NIR, near-infrared; FT-NIR, Fourier transform near-infrared spectroscopy; FCM, fuzzy c-means; KHM, k-harmonic means; GK, Gustafson–Kessel; CLSM, confocal laser scanning microscopy; GC-IMS, gas chromatography–ion mobility spectrometry; TBARS, thiobarbituric acid reactive substances; GLCM, gray-level co-occurrence matrix; LSTM, long short-term memory; FTIR, Fourier transform infrared spectroscopy; VNIR-HSI, visible–near-infrared hyperspectral imaging; NIR-HSI, near-infrared hyperspectral imaging; TVC, total viable count; SWIR-HSI, short-wave infrared hyperspectral imaging; MSI, multispectral imaging; APC, aerobic plate count; ViT-CNN, vision transformer–convolutional neural network; SVR, support vector regression; SERS, surface-enhanced Raman spectroscopy; LF-NMR, low-field nuclear magnetic resonance.

## 7. Comparative Evaluation and Selection of Detection Technologies

Meat quality evaluation involves different indicators such as appearance, composition, freshness, tissue structure, sensory attributes, authenticity and safety hazards. The relationship between these indicators and sensing signals varies. Technology selection should first consider whether the target attributes can be effectively represented by the corresponding sensing information. Surface color, texture, and morphology can be directly obtained through images. Compositional attributes such as moisture, protein, and

fat content can be indirectly characterized through spectral or electrical responses. Changes in putrefactive odors and tastes require gas-phase and liquid-phase sensing information, respectively. For water migration, cell integrity, and internal tissue changes, ultrasound, electrical detection, and LF-NMR can provide information that is difficult to obtain by optical methods; for residues, contaminants and specific microorganisms, sensing methods with selective recognition elements are more targeted. Therefore, the applicable scope of different technologies is mainly determined by the correspondence between target attributes and sensing information, rather than by the accuracy of a single model.

After the sensing information is determined, the sample status and detection conditions further limit the practical application of the technology. There are differences in surface uniformity, internal structure, and volatile release between intact meat samples, minced meat, processed meat products, and packaged meat products, making it difficult for the same model to directly cover all product forms. Temperature, humidity, surface moisture, fat distribution, packaging materials, and lighting conditions during production can also alter the sensing response. Some technologies enable direct signal acquisition, while others include steps such as headspace equilibration, liquid extraction, probe reaction, or sensor cleaning. Thus, detection speed includes not only the instrument readout time but also the time required for sample processing, signal recovery, and model inference. The rapid measurement results obtained in the laboratory are relevant to online deployment only if they remain stable under the complete operating process and actual environment.

The maturity of the validation evidence determines whether the sensing signals can be further used for quality decisions. Most studies first establish calibration relationships using traditional physical, chemical, microbiological, or sensory results, and then evaluate model performance through in-house testing. High accuracy obtained by random partitioning can demonstrate the feasibility of the method within the current dataset, but its scope of application is still limited by meat species, cuts, batches, instruments, and environmental conditions. Validation across independent batches, equipment, and production conditions can more fully reflect the actual stability of the model. Multi-source fusion can increase information coverage, but when the new information is highly correlated with the original data, or when there is acquisition asynchrony and sensor drift across devices, the fusion model may not be better than the single-source model with a simpler structure.

Taken together, non-destructive detection technologies are more suitable at this stage for tasks such as rapid screening, quality grading, and process monitoring. For safety indicators involving regulatory limits, confirmation of microbial contamination, and final adjudication of disputed samples, standard physicochemical analysis, chromatography, mass spectrometry, or microbial detection methods must still be used for confirmation. The selection of technology in practical applications should sequentially consider target attributes, sensing information, sample status, detection environment, validation level, and implementation cost, and determine the use of a single sensor, multi-technology joint characterization, or multi-source fusion system accordingly. Figure 3 compares the relative suitability of major technologies based on detection speed, sample handling, equipment and operating costs, online potential, and application maturity.

| Technology                       | Information                                           | Prep.     | Speed    | Device cost | Running cost | Sensitivity | Transfer | Portable | Online use | Maturity | Economic potential | Best use                                            |
|----------------------------------|-------------------------------------------------------|-----------|----------|-------------|--------------|-------------|----------|----------|------------|----------|--------------------|-----------------------------------------------------|
| Vis-NIR/NIR spectroscopy         | Composition + Color                                   | Minimal   | Fast     | Medium      | Low          | High        | High     | High     | High       | High     | High               | Composition, freshness, and authenticity screening  |
| Raman spectroscopy               | Molecular structure + Composition                     | Minimal   | Moderate | High        | Low          | Medium      | Medium   | Medium   | Medium     | Medium   | Medium             | Molecular-structure and composition assessment      |
| SERS                             | Specific analytes                                     | Extensive | Slow     | Medium      | High         | High        | High     | Medium   | Low        | Low      | Medium             | Targeted screening of specific hazards              |
| Intrinsic fluorescence           | Composition + Molecular microenvironment              | Minimal   | Fast     | Medium      | Low          | High        | High     | High     | Medium     | Medium   | High               | Freshness and intrinsic-fluorescence fingerprinting |
| Probe-based fluorescence sensing | Specific analytes                                     | Moderate  | Moderate | Low         | Medium       | High        | Medium   | High     | Medium     | Low      | Medium             | Targeted additive or contaminant detection          |
| RGB machine vision               | Color + Texture + Morphology                          | None      | Fast     | Low         | Low          | High        | Medium   | High     | High       | High     | High               | Appearance inspection and automated grading         |
| Multispectral imaging (MSI)      | Color + Spectral response + Spatial information       | Minimal   | Fast     | Medium      | Low          | High        | High     | High     | High       | Medium   | High               | Online screening and targeted attribute detection   |
| Hyperspectral imaging (HSI)      | Composition + Spectral response + Spatial information | Minimal   | Moderate | High        | Medium       | High        | High     | Medium   | Medium     | Medium   | Medium             | Quality visualization and anomaly localization      |
| Electronic nose                  | Volatile-odor fingerprint                             | Moderate  | Moderate | Medium      | Medium       | High        | High     | High     | Medium     | Medium   | High               | Spoilage, off-odor, and shelf-life screening        |
| Electronic tongue                | Water-soluble taste response                          | Extensive | Slow     | Medium      | Medium       | Medium      | High     | Medium   | Low        | Low      | Medium             | Taste and processing-quality assessment             |
| Ultrasonic detection             | Tissue structure + Acoustic response                  | Minimal   | Fast     | Medium      | Low          | Medium      | High     | High     | Medium     | Medium   | High               | Tissue-structure assessment and process monitoring  |
| Impedance/dielectric sensing     | Cell integrity + Water/ion mobility                   | Minimal   | Fast     | Low         | Low          | High        | High     | High     | High       | Medium   | High               | Freeze-thaw, freshness, and moisture screening      |
| LF-NMR                           | Water/fat state and mobility                          | Minimal   | Moderate | High        | Medium       | Medium      | Medium   | Low      | Low        | Medium   | Low                | Water-state and processing studies                  |

**Figure 3.** Comparison of detection conditions, relative costs, and application potential of different technologies for meat quality assessment. Green, yellow, and red cell backgrounds indicate relatively favorable, intermediate, and constrained application conditions, respectively. Identical text colors in the “Information” column indicate overlap in the quality information characterized by different technologies.

## 8. Conclusions and Future Perspectives

Meat quality is determined by multiple factors such as chemical composition, color, tissue structure, moisture status, microbial activity, and flavor changes. Various non-destructive detection technologies characterize these quality changes using different types of sensing information. RGB imaging is suitable for the evaluation of meat color, marbling, and surface defects; visible–near-infrared and near-infrared spectroscopy can be used for composition analysis, freshness monitoring, and authenticity screening; hyperspectral imaging further combines spectral and spatial information to display quality differences and the distribution of abnormal ingredients; electronic noses and electronic tongues capture volatile odor and liquid-phase taste information, respectively; Raman spectroscopy provides molecular-structural information, whereas fluorescence sensing and SERS offer high sensitivity to specific targets; ultrasonic, electrical, dielectric, and LF-NMR methods offer advantages for assessing tissue structure and moisture migration, as well as for evaluating the freeze–thaw state. Differences among these technologies in information types, detection targets, and application conditions together form a complementary set of tools for meat quality evaluation.

Existing research shows that non-destructive detection technology can improve the efficiency of meat quality screening, product grading, anomaly identification, and processing monitoring. The detection results usually come from the model relationship established between the sensing signal and the physicochemical, microbiological, or sensory reference measurements. The applicable scope of the model is affected by the meat type, part, sample form, storage conditions, instruments, and production environments. After thorough validation on representative samples and actual conditions, non-destructive models can support production grading, process control and batch quality judgment. For safety indicators involving regulatory limits, confirmation of microbial contamination, and final adjudication of disputed samples, standard physicochemical analysis,

chromatography, mass spectrometry, or microbial detection methods must still be used for confirmation. The resulting tiered evaluation framework can combine the high-throughput advantages of non-destructive testing with the accuracy of reference methods.

Multi-source information fusion provides a more complete information basis for evaluating complex attributes such as freshness, spoilage status, processing quality, and authenticity. Spectral, imaging, odor, taste, electrical, and moisture-state information reflects changes in meat products from different angles. The value of integration comes from the complementarity of this information. Data-level fusion can retain relatively complete original information, feature-level fusion helps integrate key representations of different modalities, and decision-level fusion facilitates the combination of relatively independent detection systems. For narrowly defined tasks such as meat color, a single compositional attribute, or moisture status, single-source systems with simple structures are usually easier to deploy; for comprehensive evaluations that simultaneously involve composition, structure, and microbial metabolism, multi-source fusion has greater application potential.

Future research should promote sensor miniaturization, portable device development, and online detection system integration, and develop a more unified evaluation framework based on standardized datasets, independent-batch validation, cross-instrument calibration transfer, and testing under production conditions. Interpretable modeling and predictive uncertainty analysis will enhance the connection between model results and meat quality change mechanisms, while lightweight algorithms and modular fusion systems will help reduce computing, maintenance, and model-transfer costs. As reference methods, sensing equipment, data specifications, and validation procedures become increasingly integrated, non-destructive detection technologies will further evolve from laboratory feasibility studies into practical tools for production screening, process monitoring, and quality decision-making [262–264].

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