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# Applications of Hyperspectral Imaging in Meat Quality and Safety Evaluation

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## ABSTRACT

Meat products are highly susceptible to safety and quality issues due to their complex structure, diverse processing techniques, and intricate supply chains. Traditional analytical methods for assessing meat quality are often time-consuming, labor-intensive, and destructive, making them unsuitable for real-time quality control in modern food production environments. Hyperspectral Imaging (HSI), an emerging non-destructive and rapid analytical technology, integrates imaging and spectroscopy to detect both physical and chemical attributes of meat. This review provides a comprehensive overview of the current applications and research developments of HSI in meat quality and safety evaluation. It explores the potential of HSI in detecting microbiological contamination, assessing quality parameters, and enhancing traceability throughout the supply chain. Furthermore, it evaluates the advancements in HSI hardware and software, and their readiness for integration into industrial settings under the framework of Food Industry 4.0. The future prospects of HSI for predictive and real-time quality control, enabling large-scale, automated meat inspection systems, are also discussed. This review highlights HSI as a promising tool that can shift the meat industry from reactive to proactive quality assurance practices.

**Keywords:** Hyperspectral imaging, meat quality, meat safety, quality assurance, rapid analytical technology

## INTRODUCTION

With the global population increasing and growing awareness about healthy eating, food safety has become a major concern. Meat products, in particular, present significant safety and health challenges due to their complex composition and diverse processing methods (Damez and Clerjon 2013). These products are highly perishable and therefore require stringent handling and storage protocols (Kutsanedzie et al. 2019). Past meat-related scandals have often stemmed from weak supply chain oversight, insufficient testing, and improper processing practices. As a result, there is a growing need for real-time monitoring during production to ensure product traceability and enhance consumer trust. The modernization of the meat industry under Industry 4.0 demands innovative evaluation methods (Sofos 2008).

Traditional meat quality assessments include sensory tests, wet chemical analyses (e.g., moisture, protein, and fat content), physical evaluations (such as pH and color), and microbiological tests using culture-based methods. These techniques require extensive sample preparation, skilled personnel, and well-equipped laboratories, making them costly and labor-intensive (Rizou et al. 2020).

Given these challenges, non-destructive analytical technologies are gaining attention for their ability to maintain production with minimal labor requirements. Unlike conventional methods, techniques like mid- and near-infrared spectroscopy (MIR, NIR) provide rapid, non-invasive assessments. Among them, hyperspectral imaging (HSI) stands out by combining spatial and spectral data to deliver comprehensive physical and chemical profiles of meat products (Fu and Chen 2019). This multidimensional information enables accurate evaluation of both the overall composition of raw meat and the distribution of specific chemical constituents. According to Kutsanedzie et al. (2019), hyperspectral imaging (HSI) has emerged as a powerful analytical tool capable of being applied across various food types, including meat. In recent years, it has gained considerable traction for analyzing meat quality and safety both in laboratory research and industrial applications. Despite its potential, the integration of HSI into existing meat production systems presents certain operational and design-related challenges, which are further elaborated upon later in the discussion.

Although several review papers (Pu et al. 2015; Feng et al. 2018; Antequera et al. 2021; Ozdogan et al. 2020) have summarized the use of HSI in research environments to assess meat quality and safety; most of these focus primarily on sensor features and past laboratory applications. They fall short of linking these capabilities to real-time industrial meat production environments. Given these gaps and the meat industry's pressing need for real-time quality monitoring tools, this article briefly discusses the future potential and application of the HSI technique in the meat industry. The objective of this review is to help readers understand the more advanced development of the HSI technique in meat safety and quality assessments in recent so that they will consider the potential application and trends of using the HSI technique in meat safety and quality evaluation.

## History of Hyperspectral Imaging (HSI)

Hyperspectral imaging (HSI) originated between the 1960s and 1980s in the fields of remote sensing and military defense, primarily developed by NASA and other space agencies for analyzing Earth's surface from satellites and aircraft. In 1985, the term "hyperspectral imaging" was formally introduced by Alexander Goetz and his team at NASA's Jet Propulsion Laboratory, who developed the AVIRIS (Airborne Visible Infrared Imaging Spectrometer), one of the first airborne sensors capable of capturing data across 224 contiguous spectral bands. During the 1990s and 2000s, advancements in sensor miniaturization and computational speed enabled HSI to expand into agriculture, environmental monitoring, pharmaceuticals, and eventually food quality analysis. Since the 2010s, its use has broadened further to include medical diagnostics, smart farming, and non-destructive testing in the food industry, particularly in evaluating meat quality. HSI is now widely used for detecting tenderness, adulteration, fat content, and spoilage in real time. Its ability to provide rapid, non-invasive assessment of both external and internal properties makes it a critical tool for modern food processing and quality control.

## Hyperspectral Imaging (HSI)

The meat industry demands rapid, non-destructive methods to assess meat safety and quality. Hyperspectral imaging (HSI), which merges spectroscopy and digital imaging, has gained significant attention in food quality control due to its speed, non-invasive nature, and environmental friendliness. Unlike traditional cameras that capture images in three bands (red, green, blue), HSI systems acquire images in dozens to hundreds of narrow spectral bands across the electromagnetic spectrum (typically from visible to near-infrared: 400–2500 nm). HSI addresses many of the challenges posed by conventional measurement techniques by enabling simultaneous acquisition of both spatial and spectral data from a sample. The output is typically a three-dimensional data cube (x, y, λ), where (x, y) denote spatial information and λ represents spectral data (Lorente et al. 2012). Each pixel in this image contains a full spectral profile, allowing detailed analysis of physicochemical properties and visual prediction across the entire sample (Gowen et al. 2007). HSI has been effectively applied to evaluate various quality parameters in meat, including pH (Jia et al. 2017), color (Jiang et al. 2018), springiness (Xiong et al. 2017), freshness (Grau et al. 2011), and hydroxyproline content (Xiong et al. 2015c). This article aims to fill that gap by reviewing recent applications of HSI in assessing meat quality and safety, examining the instrumentation involved, and highlighting the future potential and limitations of the technique. The goal is to provide a clearer understanding of HSI's advancements in poultry evaluation and encourage further research into its integration in modern meat processing.

## Mechanism of Action of HSI

Hyperspectral Imaging (HSI) is a powerful technique that simultaneously captures spatial and spectral information by dividing incoming light into hundreds of narrows, contiguous spectral bands across the electromagnetic spectrum. This results in a highly detailed "spectral signature" for each pixel, enabling precise identification of materials far beyond the capabilities of conventional RGB or multispectral imaging. Each band generates a two-dimensional image at a specific wavelength, and these are stacked together to form a three-dimensional data structure known as a hypercube. This hypercube includes spatial coordinates along the X and Y axes and spectral information along the Z-axis, which spans wavelengths from ultraviolet (UV) to short-wave infrared (SWIR).

Different scanner types are used to collect hyperspectral data, depending on the application. Push-broom scanners capture images line by line and are ideal for aerial or satellite imaging. Whisk-broom scanners work point by point and are suited for high-resolution mapping. Band-sequential systems capture data wavelength by wavelength, typically in laboratory settings, while snapshot systems collect full spectral frames instantly, making them ideal for dynamic scenes. The core of HSI lies in spectral signature analysis, where each material's unique pattern of light absorption and reflection across wavelengths is compared to known reference libraries using advanced algorithms to identify the material whether it's a mineral, crop, or tissue type.

HSI offers several significant advantages over traditional imaging methods. Unlike RGB imaging, which captures only three broad bands, HSI records a continuous spectrum with fine wavelength resolution (as narrow as 5 nm). It is highly sensitive, allowing detection of subtle spectral differences, such as early signs of crop stress or variations in mineral content. Furthermore, it enables non-destructive, remote, and label-free analysis, making it an invaluable tool in fields like agriculture, environmental monitoring, medicine, and food quality evaluation.

## Components of HSI

***Spectrometer:*** The spectrometer is a core component of a hyperspectral imaging (HSI) system, responsible for dispersing broad-spectrum light into individual wavelengths and projecting them onto a detector. HSI systems are commonly configured in three scanning modes: push broom (line scan), whisk broom (point scan), and tunable filter (image scan). Among these, the push broom configuration is most frequently used for meat quality assessment due to its efficiency in scanning entire sample lines (Kamruzzaman et al. 2015; Qin et al. 2013). In meat research, Specim's ImSpector series is widely preferred, including the V10 (400–1000 nm) and V17 (900–1700 nm) models. These spectrometers use transmission gratings and integrate seamlessly with CCD cameras to capture both spatial and spectral data. Their sealed, dust-resistant design ensures long-term stability and performance in industrial environments (Specim 2016a, 2016b). Another popular model is Headwall Photonics' HyperSpec VNIR, known for its F/2.5 Chase optical aperture, low stray light, and high signal-to-noise ratio. It is suitable for low-light conditions and offers robust performance in challenging environments (Headwall Photonics 2018).

***Camera and Lens:*** The camera is a vital component in hyperspectral imaging (HSI) systems, typically equipped with CCD (charge-coupled device) or CMOS (complementary metal oxide semiconductor) sensors. Both types use light-sensitive pixels to detect irradiance via the photoelectric effect, but they differ in how they process the signal. CCD sensors read data through a small number of uniform output nodes, providing consistent signal quality. In contrast, CMOS sensors have an amplifier at each pixel, allowing for faster data processing and reduced power consumption, though this can introduce higher fixed-pattern noise due to variability among pixels (Bigas et al. 2006; Fossum and Hondongwa 2014). While CCD sensors offer better image quality, CMOS sensors are known for their low power usage, fast transmission speeds, and high dynamic range, making them suitable for high-speed imaging. In recent years, scientific CMOS (sCMOS) technology has advanced further, offering high sensitivity, low noise, and large field of view, which are particularly useful in applications such as VNIR spectrometry and fluorescence microscopy (Katrasnik et al. 2013; Li 2016). In HSI applications for meat analysis, CCD cameras remain popular due to their superior consistency and image resolution. To enhance image acquisition, high-performance lenses, especially those from Schneider Optics, are commonly used. These lenses feature high resolution, wide spectral coatings, and durable industrial designs with precise focus control and aperture adjustment. Their robust construction and optical clarity make them ideal for maintaining image quality in research and industrial environments.

***Lighting Unit:*** The lighting unit is a crucial component of a hyperspectral imaging (HSI) system, as it provides the illumination necessary for capturing spectral information from the sample. The light interacts with the material, carrying its physical and chemical characteristics, which are then recorded by the camera through beam-splitting optics. The quality and stability of the lighting system directly influence the clarity and accuracy of the hyperspectral images obtained. HSI systems typically operate in one of two modes based on the sample and measurement goals: reflectance or transmittance. In reflectance mode, light shines onto the sample, and the reflected light—both from the surface and internally scattered—is captured from the same side as the illumination. To avoid glare from direct reflections (specular reflection), the light source and camera are set at specific angles. In transmittance mode, the light passes through the sample, and he transmitted light is collected from the opposite side (Ariana and Lu 2008; Reich 2005; Nicolai et al. 2007).

Currently, halogen lamps are the most widely used light sources in HSI systems. They emit a broad, continuous spectrum ranging from visible to infrared wavelengths without sharp peaks, making them ideal for capturing a full spectral profile (Qin et al. 2013). Halogen lamps are more efficient than standard incandescent bulbs and have a longer lifespan, thanks to the halogen gas that ensures steady illumination. However, they also produce excessive heat, are sensitive to temperature fluctuations (which can alter spectral accuracy), and can be affected by vibrations. To address these drawbacks, researchers have increasingly explored the use of light-emitting diodes (LEDs) as alternative light sources (Park et al. 2004). LEDs are energy-efficient, emit less heat, and are durable. They can also be configured in various ways (e.g., point, line, or ring sources) depending on the imaging requirement. Nevertheless, their limited spectral range remains a limitation, and halogen lamps still remain the preferred choice for applications that require a wide wavelength coverage.

***Data Acquisition Software:*** The selection of hyperspectral data acquisition software depends primarily on the type of spectrometer and camera used in the HSI system. Different manufacturers provide their own proprietary software to operate their cameras. For instance, Basler Vision Technologies cameras use Pylon Viewer for data control, while Roper Scientific cameras are managed through WinView (Princeton Instruments, Roper Scientific Inc.). In addition to manufacturer-specific tools, many researchers prefer to use SpectralCube software (ImSpector, Auto Vision Inc., USA) due to its advanced capabilities. SpectralCube is particularly effective in managing large hyperspectral datasets that exceed typical memory limits. It offers a user-friendly interface for reading, manipulating, analyzing, and exporting hyperspectral image data. The software allows users to extract subregions of interest using physical coordinates and supports combining and applying multiple data sets. SpectralCube also includes essential statistical and image processing functions such as mask creation, region of interest (ROI) extraction, spectral data smoothing, and basic algorithm application. It enables users to visualize spectral data, process large-scale files, and perform a range of essential operations efficiently, making it a versatile and powerful tool for hyperspectral image analysis.

***Data Analysis Software:*** Several software tools are commonly used for analyzing hyperspectral data, including ENVI, MATLAB, Unscrambler, and SPSS.

ENVI is a specialized software developed for remote sensing applications, built using Interactive Data Language (IDL). It provides an intuitive environment for hyperspectral image analysis, offering streamlined workflows and powerful processing tools. ENVI is widely favored for tasks such as spectral data extraction, ROI calibration, principal component analysis (PCA), and band math, making it a go-to solution for detailed spectral evaluation (Amigo et al. 2015).

MATLAB (Matrix Laboratory), developed by MathWorks, is a high-level software environment designed for scientific computing and programming. It is extensively used for processing hyperspectral data, including data preprocessing, model calibration, dimensionality reduction, visualization, and both quantitative and qualitative analysis. Its matrix-based architecture is particularly well-suited for handling the complex datasets typical in HSI.

Unscrambler is another powerful tool tailored for multivariate data analysis. It simplifies the handling of complex data through methods like regression analysis, classification, data preprocessing, and real-time visualization, making it highly suitable for extracting patterns and trends from large HSI datasets.

Finally, SPSS (by IBM) offers statistical tools that can be applied for predictive modeling, data mining, and descriptive statistical analysis of hyperspectral data, making it useful in research where statistical validation is needed. Together, these software platforms provide robust capabilities for effective interpretation and utilization of hyperspectral imaging results.

***Data Analysis Methods:*** The analysis of hyperspectral data typically involves three key stages: preprocessing, dimensionality reduction, and model development and evaluation. Preprocessing focuses on minimizing noise and enhancing meaningful features in the spectral data, which is essential for maintaining model accuracy. Common preprocessing methods include Standard Normal Variate (SNV), Multiplicative Scatter Correction (MSC), detrending, baseline correction, smoothing, and first and second derivative transformations. However, these techniques must be chosen carefully, as overly aggressive preprocessing can eliminate valuable data. Given the variability in sample types and experimental conditions, trial and error is often necessary to determine the most suitable method.

Hyperspectral datasets tend to be large, with high redundancy and strong correlations between adjacent wavelengths, leading to computational inefficiency and reduced model accuracy. To overcome this, dimensionality reduction techniques are applied to extract the most informative spectral bands. Popular methods include Principal Component Analysis (PCA), Random Combination (RC), Successive Projections Algorithm (SPA), Uninformative Variable Elimination (UVE), and Genetic Algorithms (GAs). These approaches help streamline data processing and support the development of more robust models.

The goal of hyperspectral analysis is to create either quantitative models, which correlate spectral data with specific physical or chemical properties, or qualitative models, which classify samples based on their spectral characteristics. Quantitative modeling methods include Multiple Linear Regression (MLR), Partial Least Squares Regression (PLSR), Artificial Neural Networks (ANN), Back Propagation Neural Networks (BPNN), and Least Squares Support Vector Machines (LS-SVM). For qualitative analysis, techniques such as Linear Discriminant Analysis (LDA), PLS Discriminant Analysis (PLS-DA), K-Nearest Neighbor (KNN), and K-means clustering are commonly used.

Model construction involves two sets of data: a calibration set for developing and fine-tuning model parameters, and a validation or prediction set for evaluating the model's performance on new, unseen data. Cross-validation—often through leave-one-out methods—is typically used to validate the robustness of the model during development. Model performance is assessed using statistical indicators such as the coefficient of determination ($R^2$) for calibration ($R^2C$), cross-validation ($R^2CV$), and prediction ($R^2P$); root mean square error (RMSE) for the same stages; and residual predictive deviation (RPD). An ideal model exhibits high $R^2$ and RPD values with low RMSE, and minimal discrepancy between calibration and prediction metrics.

## Applications of Hyperspectral Imaging for Meat Quality Evaluation

***Color:*** Color is a key physical attribute of fresh meat, closely linked to its physical, chemical, and sensory qualities (Francis, 1995). Hyperspectral imaging (HSI) has proven to be a reliable tool for accurately assessing meat color across various types of products. For instance, Kamruzzaman et al. (2016a) employed a line-scan visible HSI system (400–1000 nm) to evaluate color parameters in fresh beef, lamb, and pork using the CIE Lab color space as a reference. They identified six key wavelengths that were effective across all three meat types, achieving high predictive performance ($R^2p$ = 0.88; RMSEP = 1.6). This method improved detection efficiency by reducing the time needed for analysis. In addition to fresh meat, HSI has also been applied to monitor color changes in processed meats. Feng and Makino (2020) used a lab-based HSI system (380–1000 nm) to analyze sausages in casings, detecting dynamic color variations over time. The *redness value (a)** was predicted using a PLSR model, resulting in good accuracy ($R^2p$ = 0.78; RMSEP = 0.78). Unlike traditional single-point measurements, HSI provides a more consistent and repeatable way to analyze color. Furthermore, it allows for real-time monitoring of color distribution across the entire surface of the meat sample, enhancing both reliability and comprehensiveness.

***Moisture:*** Moisture content is a crucial indicator of fresh meat quality, influencing processing, storage, trading, and consumer acceptance (Cheng and Sun 2008). Traditional methods for measuring moisture are destructive and time-intensive, whereas Hyperspectral Imaging (HSI) offers a rapid, non-destructive alternative for evaluating water content in meats such as pork (Ma et al. 2017), beef (Yang et al. 2017a), and lamb (Kamruzzaman et al. 2012). For processed meat applications, Ma et al. (2017) utilized a pushbroom VIS-NIR HSI system (328–1115 nm) to estimate moisture in pork subjected to various treatments (heat-dehydration and cool-air dehydration). Using a calibrated PLS-R model, they achieved high prediction accuracy ($R^2p$ = 0.95; RMSEP = 1.46). To streamline moisture detection across multiple meat types and reduce variability from selecting different wavelengths for each type, Kamruzzaman et al. (2016b) developed a simplified MLR-based model using only ten key wavelengths. This model accurately predicted moisture in beef, lamb, and pork using a line-scan HSI system (380–1000 nm) ($R^2p$ = 0.96; RMSEP = 2.19%).

***Biogenic Amine Index (BAI):*** The Biogenic Amine Index (BAI) serves as a valuable chemical marker for assessing meat freshness, as biogenic amines are compounds that accumulate during storage and are closely linked to spoilage (Triki et al. 2018). The use of Hyperspectral Imaging (HSI) for BAI detection is a relatively new development and has so far been applied to fresh pork and processed beef products. In a study by Cheng et al. (2016), a pushbroom HSI system (400–1000 nm) was used to evaluate BAI in fresh pork. Several regression models were tested, and an optimized Multiple Linear Regression (MLR) model outperformed the full-spectrum PLS-R model, achieving high accuracy ($R^2p$ = 0.96; RMSEP = 4.87). Similarly, Yang et al. (2017a) applied two line-scan HSI systems to measure BAI in cooked beef stored under different conditions. They compared two spectral ranges—320–1100 nm and 930–2548 nm—and found that the support vector machine (SVM) model performed best in the 320–1100 nm range, with results showing excellent prediction accuracy ($R^2p$ = 0.97; RMSEP = 1.04).

***Total Viable Count (TVC):*** Total Viable Count (TVC) is a widely recognized indicator used to assess the microbial contamination level in meat, offering a scientific foundation for evaluating the hygienic status of food products (Skura 1991). Traditional chemical, physical, and microbiological methods for determining TVC are often labor-intensive and time-consuming. In contrast, Hyperspectral Imaging (HSI) provides a modern, non-destructive alternative that allows for real-time estimation of microbial load. HSI-based TVC detection has been applied successfully to a variety of fresh meat products, including pork (Huang et al. 2013), chicken (Feng and Sun 2013), and beef (Peng et al. 2011). It has also proven effective under diverse storage conditions. For instance, Zheng et al. (2017) used a line-scan Vis-NIR HSI system (400–1000 nm) to estimate TVC in chilled pork stored in high-oxygen environments, achieving excellent performance with an SVR model ($R^2p$ = 0.94; SEP = 0.46) after applying second derivative preprocessing. Similarly, Yang et al. (2017b) evaluated TVC in spiced beef using a line-scan HSI system in the 325–1000 nm range, obtaining strong predictive results ($R^2p$ = 0.934; RMSEP = 0.755). The same system was used to analyze cooked beef, where samples were accurately categorized into three freshness levels—fresh, moderately fresh, and spoiled—with a classification accuracy of 97.14% (Yang et al. 2017b). Sun ZB et al. (2020) expanded on this by predicting TVC in beef Longissimus dorsi under two different storage temperatures (4 °C and 10 °C). Using line-scan Vis-NIR HSI systems (400–1000 nm and 880–1720 nm) and data fusion techniques, they achieved strong results for both storage conditions ($R^2p$ = 0.96; RMSEP = 0.58 and $R^2p$ = 0.94; RMSEP = 0.97, respectively). The existing scientific evidence strongly supports the implementation of HSI for TVC analysis in meat processing plants, particularly if system speeds can be aligned with industrial production line rates.

***Nutritional Composition:*** Consumers increasingly demand detailed and accurate nutritional labeling, particularly regarding the fatty acid content of meat, which is a critical factor in evaluating its health value (Henchion et al. 2017). To meet this need, rapid and non-destructive methods like Hyperspectral Imaging (HSI) are gaining attention for monitoring the fat profile of meat throughout the supply chain, enabling better quality control and nutritional assessment. Although research on using HSI for fatty acid profiling in meat is still limited, the findings so far are encouraging. For example, Wang et al. (2020) applied a line-scan NIR-HSI system (900–1700 nm) to measure the concentrations of palmitic acid (C16:0) and oleic acid (C18:1 n9). Their predictive models, based on selected wavelength sets (29 and 22 wavelengths), showed strong performance ($R^2p$ = 0.91 and 0.88; RMSEP = 0.18 and 0.37, respectively). The technique also allowed for visual mapping of these fatty acids within lamb muscle tissue. In another study, Ma and Sun (2020) utilized a line-scan NIR-HSI system (1000–2000 nm) to quantify monounsaturated (MUFA) and polyunsaturated fatty acids (PUFA) in processed pork. Their results yielded respectable predictive accuracy ($R^2cv$ = 0.84 and 0.92; RMSECV = 0.79 and 0.76).

***Meat adulteration:*** Meat adulteration remains a significant issue in the meat industry, whether it occurs intentionally for economic gain or unintentionally due to mislabeling. Often, low-cost meat is substituted for higher-value meat to increase profit illegally. The type of adulteration varies across regions based on meat prices and cultural preferences (Vlachos et al. 2016). HSI has shown strong potential for detecting meat adulteration, initially targeting different meat species and more recently extending to intra-species adulteration. For instance, Kamruzzaman et al. (2016b) used a lab-based Vis-NIR HSI system (400–1000 nm) to detect chicken meat mixed into minced beef. The model accurately detected adulteration levels from 0–50% (w/w), with high prediction performance ($R^2p$ = 0.97; RMSEP = 2.45%). Similarly, Zheng et al. (2019) employed a pushbroom Vis-NIR HSI system (400–1000 nm) to detect duck meat in minced lamb, achieving excellent results using a PLSR model ($R^2p$ = 0.98; RMSEP = 2.51%). Jiang et al. (2019) studied duck adulteration in minced beef using a line-scan HSI system (380–1012 nm), and obtained robust outcomes ($R^2p$ = 0.96; RMSEP = 6.58%, LOD = 7.59%) through optimized wavelength selection. Their research also presented clear visual maps of adulteration distribution. Moving beyond inter-species detection, Jiang et al. (2019) focused on intra-species adulteration, identifying spoiled beef mixed into fresh beef using a Vis-NIR HSI system (400–1000 nm). The study yielded reliable results ($R^2p$ = 0.95; RMSEP = 5.67%). These findings confirm HSI's ability to differentiate between various meat types, as well as detect adulteration within the same species. Future work could aim at identifying minor adulteration levels (<5%) or detecting mislabeling in specialty meats, such as those with Protected Designation of Origin (PDO) status, thereby supporting meat product authenticity and quality control.

***Marbling Score:*** Marbling score is a critical parameter used to assess the quality of fresh meat and plays a significant role in grading at meat processing facilities and wholesale markets (Barbon et al. 2017). HSI has proven effective in evaluating marbling in various types of fresh meat. For instance, Aredo et al. (2017) applied a pushbroom HSI system (400–1000 nm) to predict the marbling score of beef, achieving a high correlation in their PLS-R model ($R^2p$ = 0.95; SEP = 0.3). The method demonstrated excellent classification performance, with an error rate as low as 0.08% according to Velasquez et al. (2017). HSI has also been successfully used for pork marbling evaluation. Huang et al. (2017a) utilized a line-scan HSI system (900–1700 nm) to assess marbling in the rib end of the Longissimus thoracis muscle, achieving reliable predictive accuracy ($R^2p$ = 0.89; RMSEP = 0.17).

## Potential Applications of HSI at the Stage of Slaughter and Processing Plant

The slaughter and processing stage of meat production can be divided into two phases: primary processing (including stunning, slaughtering, bleeding, scalding, defeathering, evisceration, and initial cleaning) and secondary processing (which involves cutting, deboning, portioning, packing, freezing, and storing). Certain steps—such as bleeding, evisceration, showering, freezing, and refrigeration—are recognized as critical control points due to their higher risk of contamination. Improper handling during these stages can lead to various quality issues like microbial contamination, unusual meat color, visible trauma, and metal fragment infiltration, complicating the assurance of meat safety and suitability for further processing. HSI offers a promising solution by enabling early detection of abnormalities before the meat moves on to critical processes like separation, freezing, or storage. It allows for real-time screening of defective products, enabling processors to decide whether to rework or discard them. This enhances manufacturing stability and reduces the likelihood of costly product recalls. Despite the positive results shown in research, there is still limited adoption of HSI in processing environments. Barriers include lack of technical knowledge and reluctance to integrate new systems into existing workflows. Some recent studies have explored practical HSI applications in processing plants. For example, Konda Naganathan et al. (2015) developed a prototype online AOTF HSI system (450–900 nm) to scan beef carcasses directly without cutting into them. This system achieved an 88% classification accuracy using Fisher's Linear Discriminant (FLD) models and required only 4 seconds per carcass, showing potential for inline carcass evaluation.

In another study, Dixit et al. (2021) used a snapshot VIS-NIR HSI camera to predict pH and intramuscular fat (IMF) content in beef at a processing pilot plant, obtaining prediction accuracies of $R^2p$ = 0.72 and 0.77, respectively, using PLS-R models. To address challenges from muscle fiber structure, Kucha et al. (2021) applied a lab-based pushbroom HSI system to scan three pork cuts for IMF prediction, offering flexibility across different cutting styles.

In the context of meat drying, von Gersdorff et al. (2021) used HSI (400–1000 nm) to assess moisture and color in dried beef, highlighting the technique's utility for cost-effective monitoring during drying. Lastly, Hitchman et al. (2021) extended HSI to monitor IMF changes in lamb stored for 1 to 5 years, showing that dynamic modeling, which accounts for sample variability over time, is more effective than static models—indicating the potential for adaptive HSI systems in industrial use.

## Potential Applications of HSI for Meat at the Stage of Distribution Centre

At the distribution center stage—where meat products are transported to exporters, wholesalers, or food service providers—issues such as authentication, classification, and adulteration become critically important. HSI offers promising applications to address these challenges. For authentication, Weng et al. (2021) applied an HSI system (400–1000 nm) to successfully identify both the geographic origin and breed of mutton, achieving a prediction accuracy of 95.67% using selected effective variables. Similarly, Williams et al. (2020) used a line-scan NIR-HSI system (950–2500 nm) to classify two types of game meat—Springbok and Blesbok—with a 96% classification accuracy using a PLS-DA model. In another example, Gong et al. (2017) classified three varieties of Chinese sausages using a line-scan HSI system (874–1734 nm), where the SVM model achieved over 90% accuracy. In addition to classification, adulteration prevention is a major concern at this stage due to the risk of fraudulent substitution for economic gain. One of the key advantages of HSI is that it provides both spectral and spatial information, allowing adulteration to be not only detected but also visually mapped on the product itself.

For example, Jiang et al. (2020) used a pushbroom HSI system (400–1000 nm) to detect adulteration of pork with jowl meat from the same species, achieving $R^2p = 0.91$ and RMSEP = 14% using a PLS-R model. In a related study, Jiang et al. (2021) detected offal adulteration in pork using HSI and a simplified model based on 11 key wavelengths, which yielded excellent results ($R^2p = 0.98$; RMSEP = 4.47%). Beyond animal-based adulteration, the incorporation of plant-based proteins—such as textured vegetable protein (TVP)—is an emerging issue. Rady and Adedeji. (2020) used a Vis-NIR pushbroom HSI system (400–1000 nm) to detect TVP in minced beef and pork, achieving a 100% classification accuracy. For HSI to be viable in industrial meat classification, its models must meet strict performance criteria: above 95% classification accuracy and less than 5% false-positive or false-negative rates. Achieving such standards is key for the technology's integration into real-world distribution and quality assurance workflows.

## Tenderness Assessment

Studies on the use of Hyperspectral Imaging (HSI) for predicting beef tenderness have shown mixed results, with prediction accuracy ranging from poor to good. Reported $R^2$ values vary between 0.45 and 0.88, and prediction errors span from 1.21 to 40.75 N. Early research by Cluff et al. (2008) using HSI (496–1036 nm) and Lorentzian functions reported poor prediction ($R^2cv = 0.45$), likely due to a mismatch between spectral and tenderness measurements (fresh vs. cooked samples). In contrast, Wu et al. (2012) achieved better accuracy ($R^2cv = 0.82$; error = 9.93 N) using optical scattering data from postmortem images. Peng (2008) also showed improved prediction ($R^2 = 0.88$; error = 1.21 kg/cm$^2$) using select wavelengths. A near-infrared HSI system (900–1700 nm) developed by ElMasry et al. (2012) yielded moderate performance ($R^2cv = 0.83$; RMSECV = 40.75 N) using 13 latent variables, though the high error values indicated low model robustness. Some studies focused on classifying beef into tenderness categories (tender, intermediate, tough) instead of predicting exact values, offering another practical approach for meat quality assessment.

Early efforts to predict pork tenderness using Hyperspectral Imaging (HSI) showed mixed outcomes. In one study, Barbin et al. (2012) used an HSI system in the 900–1700 nm range and developed a PLSR model based on sensory scores and spectral data from selected image regions. However, the results were unsatisfactory, with a low $R^2cv$ of 0.29 and error of 0.5, highlighting the limitations of using subjective methods for evaluating meat quality. Later, Tao et al. (2012) improved on this by incorporating parameters such as maximum attenuation, scattering area, and attenuation ratio, and developed MLR models linking these parameters to Warner-Bratzler Shear Force (WBSF). The attenuation ratio gave a much better $R^2cv$ of 0.87. Building further, Tao and Peng (2014) introduced a more advanced analysis using the Modified Gompertz Function (MGF), a four-parameter model based on light scattering characteristics. This method effectively described scattering behavior in pork meat between 470–960 nm, with key parameters ($\alpha$, $\beta$, $\varepsilon$, $\delta$) representing the hyperspectral data. The resulting model achieved a higher accuracy with an $R^2cv$ of 0.90, slightly outperforming previous models based on Lorentzian distribution functions.

### Strengths of HSI In Meat Quality Evaluation

Hyperspectral Imaging (HSI) offers several significant strengths in the evaluation of meat quality. One of its primary advantages is its non-destructive and real-time capability, allowing for rapid assessment without the need for sample preparation, thereby minimizing contamination risks and reducing laboratory costs. HSI also excels in multidimensional data acquisition, as it captures both spatial and spectral information, enabling the analysis of both external features and internal composition, including nutrient distribution. Furthermore, the technology supports simultaneous detection of multiple nutritional parameters—such as protein, fat, and moisture—through the application of sophisticated multivariate modeling. HSI also shows great potential for integration with other technologies, including nuclear magnetic resonance (NMR), gas chromatography-ion mobility spectrometry (GC-IMS), confocal imaging, and electronic noses, thereby enhancing its overall detection and analytical capabilities in meat quality evaluation.

## Challenges of HSI in Meat Quality Evaluation

Despite its advantages, Hyperspectral Imaging (HSI) faces several challenges in meat quality evaluation. Surface irregularities on meat products—such as uneven shapes or textures—can distort spectral signals, making accurate analysis difficult in real-world industrial environments. Another major issue is model transferability, as predictive models are often specific to particular equipment setups, requiring frequent recalibration when systems change, which adds time and labor. Additionally, the high cost and complexity of HSI systems, including hardware, maintenance, and upgrades, can hinder their widespread adoption, especially for real-time, full-spectrum applications. Finally, the technology generates large datasets that demand extensive storage capacity, fast processing power, and expert interpretation, increasing overall resource requirements.

## Future Perspectives of HSI in Meat Quality Evaluation

The future of Hyperspectral Imaging (HSI) lies in its broadened application scope, as the technology moves beyond laboratory research into full-scale industrial use. This transition is enabling the analysis of more complex nutritional parameters, such as detailed fat and protein profiles. To support this shift, there is a strong focus on system optimization, aiming to enhance sensitivity and resolution through advanced hardware configurations and refined operational settings. Alongside hardware improvements, enhanced data processing is playing a critical role, with the integration of machine learning and statistical tools that improve model flexibility, accuracy, and adaptability across various meat types and conditions. In line with Industry 4.0 advancements, HSI is being combined with deep learning, artificial intelligence, big data analytics, and automation to enable real-time monitoring and intelligent classification on production lines. Furthermore, the creation of centralized data repositories and collaborative efforts between researchers and industry stakeholders is accelerating the deployment of HSI technologies, ensuring faster innovation and broader implementation across the meat sector.

# CONCLUSIONS

Hyperspectral Imaging (HSI) has shown significant promise as a rapid, non-destructive method for evaluating the safety and quality of meat. This review summarized the essential hardware and software components involved in HSI systems. Current findings demonstrate that HSI can effectively assess meat quality and safety, offering the potential to reduce labor costs and enhance operational efficiency. However, while HSI techniques have made good progress in qualitative classification, their accuracy in quantitative analysis remains limited. To improve, advancements are required in both the hardware and software aspects of HSI technology. From a hardware standpoint, there is a need to enhance spectral and spatial resolution and minimize optical distortions from spectrometers and cameras. Proper lighting setup and environmental control are equally critical, especially considering the complex surface characteristics of meat, such as moisture and connective tissue, which can lead to specular reflection that compromises image quality. Further, factors like temperature and humidity control are crucial when testing large sample volumes, as biological specimens are sensitive to environmental changes. On the software side, progress has lagged behind hardware innovations. Currently, there are limited software options tailored specifically for hyperspectral data analysis. The challenge lies in managing the large volume of redundant information present in HSI datasets, which slows down analysis and may affect accuracy. Improved preprocessing techniques are needed to filter out irrelevant data efficiently. While many existing modeling methods (e.g., PLSR) are reliable and widely used, they are often too basic for advanced analysis. Combining them with modern data reduction and preprocessing tools has improved performance, but more intelligent, adaptive algorithms are needed going forward. Integrating database technologies and leveraging AI-based techniques—like machine learning and deep learning—can greatly enhance the accuracy and usefulness of HSI systems. Moreover, meat quality cannot typically be evaluated based on a single indicator alone. Issues like PSE (Pale, Soft, Exudative) and DFD (Dark, Firm, Dry) require simultaneous analysis of multiple parameters, including color, pH, and moisture. Future developments in HSI should focus on multi-parameter detection during a single scan. Researchers are also increasingly exploring the use of HSI for measuring nutritional attributes such as protein and fat content. So far, HSI research has primarily focused on post-slaughter quality assessments, yet meat quality is influenced throughout the production process. Therefore, integrating HSI with other technologies—such as machine vision for automated broiler monitoring during productions—could provide comprehensive quality control from farm to fork. Such integration will be essential to fully realize the potential of HSI in the meat industry.

## COMPETING INTERESTS

The authors have no known competing interests either financial or personal between themselves and others that might bias the work.

## ETHICS STATEMENT

Not Applicable

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