International Journal of Food Science + Technology

Review

Implementing artificial intelligence to measure meat quality parameters in local market traceability processes

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(Received 8 June 2024; Accepted in revised form 22 August 2024)

Summary The application of computer technologies associated with sensors and artificial intelligence (AI) in the quantification and qualification of quality parameters of meat products of various domestic species is an area of research, development, and innovation of great relevance in the agri-food industry. This review covers the most recent advances in this area, highlighting the importance of computer vision, artificial intelligence, and ultrasonography in evaluating quality and efficiency in meat products' production and monitoring processes. Various techniques and methodologies used to evaluate quality parameters such as colour, water holding capacity (WHC), pH, moisture, texture, and intramuscular fat, among others related to animal origin, breed and handling, are discussed. In addition, the benefits and practical applications of the technology in the meat industry are examined, such as the automation of inspection processes, accurate product classification, traceability, and food safety. While the potential of artificial intelligence associated with sensor development in the meat industry is promising, it is crucial to recognise that this is an evolving field. This technology offers innovative solutions that enable efficient, cost-effective, and consumer-oriented production. However, it also underlines the urgent need for further research and development of new techniques and tools such as artificial intelligence algorithms, the development of more sensitive and accurate multispectral sensors, advances in computer vision for 3D image analysis and automated detection, and the integration of advanced ultrasonography with other technologies. Also crucial is the development of autonomous robotic systems for the automation of inspection processes, the implementation of real-time monitoring systems for traceability and food safety, and the creation of intuitive interfaces for human-machine interaction. In addition, the automation of sensory analysis and the optimisation of sustainability and energy efficiency are key areas that require immediate attention to address the current challenges in this agri-food and agri-industrial sector, highlighting and emphasising the importance of ongoing innovation in the field.

Keywords Artificial intelligence, computer vision, hyperspectral imaging, meat quality, Ohmic, ultrasound.

Introduction

In recent decades, technology has been indispensable in the globalised industry. Artificial intelligence (AI) has developed practical, fast, and efficient tools an devices to assess quality and detect problems in the food, agriculture, and livestock industries; acquiring unprecedented importance in our daily lives (Kutyauripo *et al*., 2023).

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Artificial intelligence (AI) is transforming the meat industry by introducing advanced techniques that enable more accurate and efficient assessment of meat quality. Traditionally, meat quality assessment has relied on manual and subjective methods, such as visual inspection and physical testing, which can be inconsistent and time-consuming. However, with the advent of AI, it is now possible to use advanced machine learning models to analyse complex data and provide more objective and faster assessments. For example, hyperspectral images, which capture detailed

doi:10.1111/ijfs.17546

spectral information across many bands of light, can be processed by AI algorithms to identify molecular properties invisible to the human eye (Wang & Li, 2024). This improves the accuracy of quality assessment and enables real-time detection of characteristics such as freshness, fat content, colour, and texture of meat, thereby optimising quality control. More importantly, it significantly reduces waste, a crucial step towards a more sustainable meat industry. Consequently, AI plays a crucial role in modernising meat science, leading the industry into a new era of innovation and efficiency (Kakani *et al.*, 2020).

Furthermore, these IA technologies are vital for guaranteeing product quality, safety, and authenticity concerns across the agri-food industry (Othman *et al.*, 2023). Creating large volumes of data, better known as 'Big Data', opens up new opportunities for monitoring and inspecting agricultural and food processes and, in conjunction with artificial intelligence, transforming agri-food systems through spectral methods and sensor fusion (Misra *et al.*, 2022). These techniques have developed rapidly in the last four years due to growing concerns about food quality and safety. This trend is expected to continue progressively in the coming years as the demand for food continues to rise imminently, with a focus on food safety and quality (Mavani *et al.*, 2022; Zhang *et al.*, 2023), as well as meat quality management under automation (Esmaeily *et al.*, 2024).

Conventional techniques for assessing meat quality are time-consuming, destructive, and prone to inconsistencies and variability. The introduction of instrumentation technology has significantly improved this process, allowing for the swift identification of meat characteristics. This has led to enhanced control and grading of products in mechanised processes. These advancements have attracted considerable interest form both that have attracted the food industry and consumers, who place a high value on safety and quality in the meat industry. With its superior accuracy, instrumentation technology enables the assessment and optimisation of a range of meat quality parameters, including tenderness, water holding capacity, moisture, colour, intramuscular fat composition, and freshness. This accuracy is a key advantage over manual methods (ElMasry *et al.*, 2012; Sanchez *et al.*, 2022).

Furthermore, AI enables data integration from disparate sources, facilitating a comprehensive assessment considering animal origin, storage conditions, and production processes. Implementing 'Food Quality 4.0' or Industry 4.0, is transforming food quality is based on digitisation, optimisation, simulation, and automation of analyses through advanced methods and technologies in the food industry. This ensures more rigorous quality control that is adaptable to the needs of the modern market (Hassoun *et al.*, 2023).

Advanced techniques to improve food quality include non-destructive finger printing methods, the internet of things (IoT), cloud computing, Ohmic technologies, bioinformatics tools, artificial intelligence, and big data; likewise, hyperspectral imaging (HSI), visible and near-infrared spectroscopy (VIS/NIR), magnetic resonance imaging (MRI), X-ray, and ultrasound are widely used for their ability to inspect quickly and non-destructively (Lim *et al.*, 2021), being of great use in the development of multispectral systems, which provide characteristic wavelengths to predict various meat attributes (pH, colour, water holding capacity, shear strength, chemical, and sensory composition) as real-time food quality assurance (Pu *et al.*, 2015; Zhang *et al.*, 2023).

Computer image analysis is a fast, non-destructive, replicable, and repeatable method for assessing agri-food and meat quality characteristics. Also, the use of artificial neural networks (ANN) improves food traceability (Wang *et al.*, 2017; Cernadas *et al.*, 2022). The review's objective is to analyse the potential of sensors and artificial intelligence in measuring quality parameters of meat products, and how these technologies can improve quality monitoring and management in local markets, highlighting their relevance for the food sector.

Meat production

The quality of meat is evaluated internationally using a measurement of the quality of intramuscular fat present in the *longissimus dorsi* muscle, which serves as a primary quality indicator. In the 1980s, video imaging solutions were introduced to analyse carcass characteristics, thereby providing a more advanced and objective method of assessing meat quality. Nevertheless, in Peru, the prevailing procedures remain manual and subjective, with specialists relying primarily on visual inspection and needing access to contemporary image processing (Schulz & Sundrum, 2019). This lack of updating represents a limitation in the accuracy of meat quality assessment (Cardenas *et al.*, 2024). The implementation of automated tools and AI technologies has the potential to transform the grading process, enhancing consistency and objectivity in meat assessment. This is particularly significant in a country like Peru, were livestock production is not just an industry, but a pivotal part of the local economy (Radolf *et al.*, 2022). However, there has not been a decline in cattle profit and an increase in pork consumption (Table S1), where per capita meat consumption is considered to have declined over the last five years (Figure S1); this decline in meat consumption can be attributed to factors such as the COVID 19 pandemic , as well as the quality of products in the markets.

Methodologic

The following article was based on a comprehensive review of selected articles from the last ten years to ensure the inclusion of the most recent and relevant technological developments in the measuring of meat quality parameters. The review concentrated on identifying and assessing both emerging and established technologies for determining a range of meat quality parameters, including pH, water retention capacity, colour, tenderness, and others.

Artificial intelligence in food control

Since the beginning of history, the evolution of humanity has been reflected in the management and use of various applications, industrialisation, and technologies employed in each era to meet the needs of an ever-changing world. Artificial intelligence (AI) has been a broad field since its inception, ranging from philosophical musings to practical, real-world applications (Holzinger *et al*., 2023); it went through a "winter" in 1980, which oscillated between high expectations and disappointments as industry and many scientists viewed it with scepticism, yet AI research has continued to progress to the present day (Hendler, 2008).

The most recent advance in AI, computer vision (CV) image processing, has the potential to revolutionise the meat industry and supply chain management, and mathematics, its application in digital image analysis has expanded beyond identifying external quality factors (Brosnan & Sun, 2004; Taheri-Garavand *et al*., 2019). The role of CV in facilitating model identification, service generation, and decision-making processes underline its relevance in meeting the evolving requirements of the food and meat industry (Nath *et al*., 2024).

Computer vision methods offer a practical and efficient means of quality monitoring in the meat and food industry (Sandberg *et al*., 2023). These systems can analyse food without the need for large samples or chemicals, providing objective results in a fast and non-invasive manner (Jia *et al*., 2024). They utilise various image-capturing devices, such as digital cameras and computed tomography, to analyse macro and microscopic digital images (Jimoh *et al*., 2023). This technology is constantly evolving and improving to meet the industry's needs (Modzelewska-Kapituła & Jun, 2022; Kaushal *et al*., 2024).

Using robotics in the meat-cutting industry presents an effective automation alternative that improves the accuracy, efficiency, and reliability of elementary operations in the food industry (Wright *et al*., 2024). Integrating vision sensors, force sensors and AI with cutting robots optimises their operation (Aly *et al*., 2023; Xu *et al*., 2023). The application of AI in robotics facilitates movements and integrates algorithms and models that extend their autonomy. These applications present several challenges and advantages in primary cutting processes in meat production (Purnell and (Gifhe), 2013; Hwa & Chuan, 2024).

AI-based computer vision has been a game changer in the agri-food sector; it identifies and grades meat cuts with a speed and accuracy that surpasses traditional methods, ensuring that each cut meets the desired quality standards. The use of AI in beef, pork, and mutton grading serves as a prime example of its efficiency. High-resolution cameras and deep learning algorithms swiftly analyse visual characteristics, including colour, texture, and intramuscular fat, enabling faster and more accurate grading processes than traditional manual methods (Shi *et al*., 2021). Furthermore, in supply chain management, the application of AI has led to significant advances in terms of traceability and quality control. For example, AI systems integrated with RFID sensors and blockchain technology facilitate accurate tracking of the provenance and storage circumstances of meat products throughout the supply chain, helping to ensure food freshness and safety by applying advanced technologies (Tsolakis *et al*., 2023).

Meat quality quantification

Given its importance as a vital protein source in the human diet, meat is mainly valued for its sensory quality, and colour is one of the most relevant attributes for producers and consumers alike (Table S2). The visual aspect of food is of paramount importance for evaluating its quality, with the meat colour being significantly influenced by myoglobin (Mb) and the associated chemical processes, which play a pivotal role in the perception of quality (Sanchez *et al*., 2022). Food quality depends on its surface appearance and colour, which reflect the product's physical, chemical, and sensory properties (Francis, 1995). The $L^*a^*b^*$ colour space, a three-dimensional model that represents colour in terms of three values: L^* for lightness, a^* for the colour green to red, and b^* for the colour blue to yellow, is a widely used standard due to its uniformity and alignment with human colour perception (Konovalenko *et al*., 2021). Combining this colour space with linear, quadratic, gamma, and neural network models for RGB conversion has significantly improved quality control, reinforcing established standards within the meat industry (León *et al*., 2006).

The meat industry requires dependable data on meat quality throughout the production process to guarantee the delivery of premium products (Botilias *et al*., 2023).

Various techniques based on electromagnetic waves are employed to assess sensory attributes, chemical composition, and physicochemical properties of meat. Hyperspectral imaging (HSI) is a technique that employs electromagnetic radiation to obtain a comprehensive spectrum of data, which can then be analysed to gain insights into a given sample's chemical and physical composition. Combining HSI with multivariate analysis represents an efficient, accurate, and non-invasive tool for the real-time monitoring of meat attributes. This allows for integrating conventional and spectroscopic images, providing spatial and spectral information respectively, highlighting its effectiveness in the assessment of muscle *tenderness* in beef, pork, and lamb (Kamruzzaman *et al*., 2015; Kucha & Olaniyi, 2024).

In order to evaluate the essential characteristics, various techniques based on electromagnetic waves are used, ranging from sensory attributes to chemical composition and physicochemical, sanitary, and nutritional properties (Kharbach *et al*., 2023). These techniques range from low- and high-frequency impedance measurements, microwaves, nuclear magnetic resonance (NMR), infrared, and ultraviolet light to X-ray interactions, involving physical interactions between electromagnetic waves (Damez & Clerjon, 2013). These non-invasive techniques focus on developing electronic and computerised methods to obtain objective data based on specific signals generated by devices that interact with meat samples at the atomic or molecular level, which are detected and analysed quantitatively, providing information on tissue depth, volumes, and distribution of fat and muscle; these signals can be electromagnetic generated by ultrasound, X-ray computed tomography (CT), or radiofrequency such as MRI, being beneficial for meat and animal selection programmes (Scholz *et al*., 2015).

Low-power ultrasound (LPU), together with spectroscopy and magnetic resonance imaging (MRI), are non-destructive and practical analytical methods widely used to estimate the composition of various products in the meat industry and to control the physicochemical properties, improving quality and preventing fraud and adulteration in the sector. In addition, meat analogues can mimic the sensory properties of meat, contributing to the reduction of consumption (Kołodziejczak *et al*., 2021). Therefore, several methods of texture and structure analysis of meat and meat analogues were analysed, including mechanical tests such as texture profile analysis, spectroscopy such as NMR and hyperspectral imaging techniques (Awad *et al*., 2012; Schreuders *et al*., 2021). Numerous studies have combined magnetic resonance imaging (MRI) techniques, computer image analysis and regression methods; these techniques are used to predict a wide range of physicochemical and sensory attributes in Iberian ham and pork loin, as well as to identify muscles, *biceps femoris*, and *semimembranosus tissue*, providing a quantitative assessment of volume, moisture, and weight during the maturation process; Furthermore, it allows the identification of muscles using computer vision techniques, complementing quality analysis, and optimising yield measurement methodologies, which have demonstrated reliability in the automatic system for predicting the quality of meat products (Antequera *et al*., 2007; Ma *et al*., 2016; Ávila *et al*., 2019).

The hyperspectral imaging technique in the near-infrared (NIR) region was used to assess the quality of pork meat attributes in *longissimus dorsi* (LD), *semimembranosus* (SM), *semitendinosus* (ST), and *biceps femoris* (BF) muscle; representative spectral information was obtained to predict colour characteristics (*L*, *a*, *b*, chroma, and hue angle), drip loss, pH, moisture, fat, and sensory characteristics using partial least squares regression models (PLS-R). This technique was applied to determine the chemical composition and microbial quality of intact and minced meat during refrigerated storage, obtaining accurate statistical models to predict total viable count (TVC) and psychotropic plate count (PPC) in meat industry quality control. Subsequently, the potential of the VIS/NIR region together with deep learning (CNN) and multivariate analysis was investigated to identify specific wavelengths relevant to real-time monitoring of water holding capacity (WRC), fat, protein, and adulteration levels in fresh beef, lamb, and pork by developing partial least squares regression (PLSR) and least squares support vector machine (LS-SVM) models; hyperspectral imaging coupled with chemometric analysis has the potential to assess multiple chemical components simultaneously without the need for hazardous chemical reagents (Barbin *et al*., 2012, 2013; Kamruzzaman *et al*., 2015; Zhao *et al*., 2019; Zhang *et al*., 2022).

Texture analysis methods include mechanical tests such as texture profiles and hyperspectral imaging techniques. The techniques permit the evaluation of muscle tenderness in beef, pork, and lamb, facilitating the generation of tenderness distribution maps and shear force measurements. Shear force in *longissimus* muscle steaks from Nellore cattle was evaluated using HSI as a non-destructive method in meat control by creating tenderness distribution maps and measuring Warner-Bratzler shear force (WBSF) and shear force in cut (SSF) using chemometric techniques (Balage *et al*., 2018), such as partial least squares and discriminant analysis (PLS-DA) (León-Ecay *et al*., 2022).

Water holding capacity (WHC) is a pivotal parameter that considerably influences meat quality. To ascertain this parameter, spectroscopic measurements are conducted utilising a fibre optic probe (FOP), a VIS/NIR reflectance spectrophotometer and a low-field 1 H nuclear magnetic resonance (LF-NMR) instrument. These instruments are employed to evaluated both the water holding capacity (WHC) and the chemical composition of the pigs, with particular attention paid to the halothane gene carriers in the *longissimus dorsi* and *semitendinosus* muscles (Brøndum *et al*., 2000).

The distribution of intramuscular fat, or marbling, significantly influences meat quality. VIS/NIR spectroscopy and magnetic resonance imaging (MRI) are non-destructive techniques employed to estimate intramuscular fat content and fatty acid composition in lamb *longissimus lumborum* muscle and pork in the *longissimus dorsi* and *semimembranosus* muscles. The techniques in questions employs partial least squares regression (PLSR) analysis, which enables the accurate prediction of several quality aspects, including pH, intramuscular fat content (IMF), and fatty acid (FA) composition. These methods provide valuable information on marbling and facilitate the identification of meat quality (Andersen *et al*., 1999; Craigie *et al*., 2017; Lambe *et al*., 2021). Moreover, the FOSS FoodScan™ spectrophotometer with artificial neural network (ANN) calibration based on NIR spectroscopy, it highly regarded for measuring meat attributes (moisture, protein, fat, among others.). However, it is criticised for the lengthy time required for samples preparation (spraying and grinding), negatively affecting its efficiency and automation (Anderson, 2007).

Fluorescence spectroscopy represents a valuable tool offering practical applications in the analysis of the relationship between the structure and texture of pork emulsions (Allais *et al*., 2004). Furthermore, principal component analysis (PCA) and canonical correlation analysis (CCA) techniques are employed (Salgado Pardo *et al*., 2024), thereby enabling the identification of fat/meat interaction and the classification of meat cuts. Furthermore, this technique has been employed to assess the chemical properties and colour characteristics ($L^*a^*b^*$) of raw and dried meat from *gluteus medius* (GM), *longissimus thoracis* (*LT*), *and semitendinosus* (*ST*) muscles from yak (*Bos grunniens*) carcasses 24 h post-slaughter. Colour was quantified regression PLSR models demonstrated the emission spectra of tryptophan, vitamin A, and riboflavin can be used to reliably predict water activity, moisture, fat, and colour (Allais *et al*., 2004; Ozbekova *et al*., 2024).

In the maturation process of beef, the behaviour of electrical anisotropy has been studied to determine the degree of ageing by assessing several muscles, such as *semimembranosus*, *rectus abdominis*, *semitendinosus*, and *pectoralis profundus*, using a method with aligned electrode sensors to measure linear impedances and contact impedances; this analysis showed a correlation between the linear impedance index and the resistance of muscle fibres, suggesting its usefulness in predicting meat maturation (Damez *et al*., 2008).

Emerging dielectric technologies, such as radio frequency (RF), surface cold plasma (SCP), and pulsed electric field (PEF), have proven to be instrumental in determining treatment efficacy in meat samples, impacting their safety, nutrition, and quality. Dielectric spectra at low frequencies have been used to predict meat quality PSE (pale, soft, and exudative), DFD (dark, firm, and dry), RFN (firm red and non-exudative), and ageing progress in porcine muscles (*longissimus dorsi*) in raw and salted samples, positively affecting meat tenderness and flavour; principal component analysis (PCA) was used to analyse the relationships between physical-biochemical parameters and dielectric properties of meat, allowing the evaluation of parameters such as salt content, moisture, water holding capacity, and volume, through the salting treatment operation of high-quality meat products (Castro-Giráldez *et al*., 2010; Bekhit *et al*., 2023).

The quality of minced beef during storage using digital consumer cameras, the meat samples were captured using spectral images such as RGB (Yang *et al*., 2017). The information from these spectral images was reconstructed as a reference for microbiological and bacterial analysis of pre-packaged meat (King *et al*., 2023). On the other hand, a RAW and JPEG image analysis model was developed to estimate pork loin mean surface area, fat thickness, meat colour, and marbling, using RGB (red, green, and blue) and HSB (hue, saturation, and brightness) images and converted to $L^*a^*b^*$ colour space, revealing that marbling at the back end of the loin is most closely related to % IMF (Orava *et al*., 2012; Uttaro *et al*., 2021).

Fat is an indispensable component of meat, influencing its taste, texture, and nutritional value. Fluorescence spectroscopy and targeted mass spectrometry facilitate assessing fat composition and identifying biomarkers associated with meat quality. Consequently, the utilisation of sophisticated proteomic analysis techniques, including reverse phase protein analysis (RPPA) and parallel reaction monitoring (PRM) mass spectrometry, has facilitated the assessment of protein biomarkers associated with meat quality. This has enabled the identification of biomarkers linked to beef tenderness, marbling, and shear force variability. The samples evaluated were derived from the *longissimus thoracis*, *semimembranosus*, *rectus abdominis*, *triceps brachii* and *semitendinosus* muscle. Moreover, the potential of RPPAs in quantifying meat attributes using biomarkers has been emphasised, contributing to a more comprehensive understanding and management of meat quality (Gagaoua *et al*., 2018; Picard *et al*., 2019; Bonnet *et al*., 2020).

Quality observation models

Universal calibration models for prediction include partial least squares regression, support vector machine and deep convolutional neural networks, which are effective in predicting intramuscular fat and pH content in red meat, regardless of species and muscle type (Kamruzzaman *et al*., 2015; Sun, 2016; Dixit *et al*., 2021). On the other hand, image processing is fundamental in machine vision, with hyperspectral imaging (HSI) being a tool for non-destructive analysis of meat quality and safety by generating a wide range of spectral and spatial data for analysis (Hsu *et al*., 2017; Azarmdel *et al*., 2019; Jia *et al*., 2022). The combination of spectroscopy imaging with deep learning models, particularly convolutional neural networks (CNN), will prove to be effective in spectral analysis, providing a comprehensive solution for assessing food quality, considering that the convolutional neural network technique represents innovation in data evaluation because of its ability to handle complex data automatically, demonstrating better performance with conventional chemometric methods (Acquarelli *et al*., 2017; Luo *et al*., 2024).

Band selection methods contribute to improving the performance of total viable count (TVC) prediction models using PSLR by reducing the processing time required to evaluate HSI data; the reliability of importance variable projection (VIP), selectivity ratio (SR), and Monte Carlo variable selection (EMCVS) methods in band selection for HSI data was demonstrated in meat supply chain monitoring (Achata *et al*., 2020). While the 3D deep convolutional neural network (3D-CNN) model is designed to extract combined features and classify meat in HSI images, in addition to introducing an innovative graph-based post-processing method to improve the predictions of the 3D-CNN model. Despite the inherent limitations of HSI spectral information, this model exhibits a robust classification capability for red meat, with an accuracy of 96.9% for near-infrared (NIR) HSI and 97.1% for visible light (VIS) (Al-Sarayreh *et al*., 2020).

Comparison of technologies for quantifying meat quality

Traditional spectroscopy methods, with their focus on point measurements, provide a limited view of the quality of the object of study. In contrast, HSI combines spectral scanning with imaging technology, allowing the acquisition of hundreds of continuous spectral bands. This visualises the spatial distribution of quality parameters and provides detailed information on characteristics such as size, shape, colour, marbling, and texture. Importantly, HSI is not static but continues to evolve, overcoming traditional challenges and pushing the boundaries of meat quality assessment. Digital images, on the other hand, offer spatial information on meat quality, such as appearance, size, and colour. But what sets it apart is the computer-based imaging technology, which enhances the efficiency and objectivity of meat quality assessment, providing a reliable and consistent evaluation (Tang *et al*., 2023; Jo *et al*., 2024).

The limitations in deep learning (DL) models for processing high-dimensional hyperspectral image (HSI) data are primarily due to the limitations of convolutional neural networks (CNNs) in capturing global relationships and the challenges associated with recurrent neural networks (RNNs) in handling evanescent gradients and long-term dependencies. Convolutional neural networks (CNNs) concentrate on local features with a restricted receptive field and are highly complex due to using three-dimensional convolutions. In contrast the RNNs are less proficient in spatial representation. A novel approach, the hyperspectral image classification model with continuous shape computing (HIS-CfC), has been developed to address these limitations. This approach produces results comparable to those of existing methods and reduces the size of the model, suggesting significant improvements in the efficiency and effectiveness of HSI classification; HIS-CfC employs an innovative approach that combines spectral data-specific tokenisation and an optimised architecture comprising fully connected and convolutional layers. This enables the capture of both local and global features with greater efficacy. The model has demonstrated superior performance to traditional models, achieving a macro average score of 99.11% with a significantly more compact model (1.11 MB vs. 46.01 MB for CNN). This reduction in storage and processing overhead has been achieved without sacrificing accuracy, reassuring the audience about its practicality and cost-effectiveness (Zhang & Abdulla, 2024). Furthermore, the outcomes yielded by HIS-CfC effectively predict drip loss, pH, and colour of pork, thereby exemplifying its capacity to classify pork based on its exudation and colour characteristics; this provides an objective and reliable alternative demonstrating its versatility and effectiveness in industrial applications (Qiao *et al*., 2007).

Machine vision technology captures images and converts them into digital data to detect characteristics such as marbling, tenderness, freshness, and colour. In contrast, hyperspectral technology captures images at multiple wavelengths, providing visual and chemical information about the sample. Finally, multisource information fusion technology integrates data from various sensors to improve meat quality assessment; this technology overcomes the limitations of using a single sensor, providing a more accurate and objective evaluation by combining data, characteristics, and decision-making levels, thus achieving a comprehensive assessment of meat quality (Xu *et al*., 2024).

Ultrasonography in meat quality

The most recent use of ultrasonography is in the meat industry, being ultrasonography a means of evaluation and diagnosis in the productive and reproductive processes, as well as in estimating the composition and quality of beef and sheep meat (Silva, 2017; Lazăr *et al.*, 2022). In the productive process, ultrasound measurements are made of the *longissimus dorsi* (*LD*) muscle and subcutaneous fat to evaluate the area and depth of the muscle (Fabbri *et al.*, 2021).

High-intensity ultrasound (HIU) is an emerging technique in meat quality (Valenzuela *et al.*, 2021). It is considered "green" to conventional methods of beef preservation by influencing the physicochemical properties of meat (Lee *et al.*, 2023), evaluating parameters of colour ($L^*a^*b^*c^*$, and Hue*), drip loss, water holding capacity, and shear strength in fresh and processed meat muscles. These parameters are related to tenderness and meat quantity, such as Rib eye area, intramuscular fat percentage, and backfat thickness, employing multivariate data analysis to improve meat quality and shelf life (Nunes *et al.*, 2015; Caraveo-Suarez *et al.*, 2023).

By using real-time ultrasound (RTU) imaging to predict intramuscular fat percentage (IMF) in Charolaise cattle, ultrasound scans are performed on the *longissimus dorsi* (*LD*) muscle using a portable ultrasound scanner (MyLabOne™, Esaote S.p.a., and a Pie 200SLC) scanner for the thoracic vertebrae, to obtain *in vivo* ultrasound images, in addition, linear discriminant analysis is performed on the texture to identify the key variables that best predict the percentage of GMI, as essential indicators in predicting carcass composition and value in cattle (Aass *et al.*, 2006; Conroy *et al.*, 2010; Fiore *et al.*, 2020).

Low-frequency, high-power ultrasound treatments (40 kHz, 1500 W) on meat quality and connective tissue collagen in beef *semitendinosus* muscle improve tenderness and sensory characteristics of meat by positively influencing exudate yield, water loss rate, cooking loss, meat tenderness, and connective tissue collagen properties (Chang *et al.*, 2015). In addition, mathematical equations and models have been developed to describe marbling change in Japanese Black steers, using longitudinal measurements that fit a nonlinear logistic curve, being useful for genetic improvement. Also, it has been explored how genomic regions influence meat quality properties such as intramuscular fatness in Nellore cattle, identifying genes and chromosomes relevant to this trait, which has contributed to understanding the contribution of genetic information associated with its phenotypic expression (Martins *et al.*, 2021; Tokunaga *et al.*, 2021). Ultrasonography can be one of the most suitable tools for evaluating the characteristics of animals' meat prior to slaughter. This tool should be implemented in production centres or livestock farms, thus guaranteeing the final destination of the products and the processing of the animals so that good quality products reach the market.

Limitations of the technology

Although artificial intelligence (AI) has improved production efficiency and supply chain management in the agri-food industry by enabling accurate predictions and reducing the risk of contamination, its application faces significant limitations. High costs, the need for specialised expertise and cultural resistance are vital obstacles. Moreover, AI, driven by predefined commands, can only partially replace humans in complex tasks, and its dependence on human intervention may limit its adaptability. There are also cybersecurity risks that add vulnerability to automated processes (Thapa *et al.*, 2023).

The application of AI can reduce industries' carbon costs by optimising energy use and identifying inefficiencies. However, the application of AI comes with costs and limitations. The initial adoption of these technologies can be costly, requiring investments in technology infrastructure, staff training, and the development of specific algorithms. However, it's important to remember that the long-term benefits of reduced carbon costs and improved operational efficiency make AI a reassuring investment for agri-food and industrial industries committed to sustainability, technological advancement, and the environment (Tseng & Lin, 2024).

Conclusions

The use of sensors and artificial intelligence techniques in the measurement of meat product quality has been shown to significantly improve precision and efficiency in the evaluation of parameters such as intramuscular fat, water holding capacity, moisture, colouration, shear force, pH, among others; allowing real-time monitoring, facilitating early detection of quality problems and improving traceability throughout the supply chain. In local markets, the implementation of sensors and AI can increase the competitiveness of producers by providing reliable data on the quality of their products in the meat industry. The meat industry in Peru is advancing considerably, and implementing the mentioned technologies will support better control of the quality parameters of meat products in a systematic and fast way, strengthening traceability, thus guaranteeing safety and quality, and increasing the consumption of meat products of high biological value.

Acknowledgments

To Project CUI 2432072: 'Mejoramiento de la disponibilidad de material genético de ganado bovino con alto valor a nivel nacional. 7 departamentos' of the Ministry of Agrarian Development and Irrigation – Peru.

Author contributions

Wuesley Y. Alvarez-García: Conceptualization; investigation; methodology; data curation; formal analysis; resources; software; supervision; validation; visualization; writing – original draft; writing – review and editing. **Laura Mendoza:** Investigation; methodology; funding acquisition; software; supervision; validation; visualization; writing – original draft. **Yudith Muñoz-Vílchez:** Formal analysis; software; validation; visualization; writing – original draft; writing – review and editing. **David Casanova Nuñez-Melgar:** Conceptualization; data curation; funding acquisition; investigation; methodology; project administration; resources; supervision; writing – original draft. **Carlos Quilcate:** Conceptualization; resources; project administration; validation; visualization; funding acquisition; supervision.

Conflict of interest

The authors declare no conflicts of interest.

Ethical approval

Ethics approval was not required for this research.

Peer review

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/ijfs.17546.

Data availability statement

Data sharing is not applicable to the article as datasets were generated or analysed during the current study.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Per capita consumption of beef, pork, and lamb in Peru.

Table S1. Peru: meat production, per capita consumption and evolution of livestock processing in processing centres by year by species, 2012–2023 (SIEA – MIDAGRI, 2024).

Table S2. Differences in those aspects have been measured with these technologies.