Review

AI-Driven Innovations in Meat Quality and Safety: Applications, Challenges, and Future Directions

Emrobowansan Monday Idamokoro

Department of Biological and Environmental Sciences, Faculty of Natural Sciences, Walter Sisulu University, Nelson Mandela Drive Campus, P/Bag X1, Mthatha, 5117, South Africa

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Corresponding Author:
Emrobowansan Monday Idamokoro
Department of Biological and Environmental Sciences, Faculty of Natural Sciences, Walter Sisulu University, Nelson Mandela Drive Campus, P/Bag X1, Mthatha, 5117, South Africa
E-mail: mondayidamokoro@gmail.com

Abstract: Artificial Intelligence (AI) is revolutionizing the meat sector by improving efficiency, accurateness, as well as sustainability in meat production, quality evaluation, and safety control. The conventional systems of meat inspection, handling, and processing are usually time consuming, labour-intensive, prone to contamination during handling and often susceptible to human errors. The use of artificial intelligence to drive technologies, including Deep Learning (DL), Machine Learning (ML), and computer vision have transformed the industry by making available automated, data-driven answers that enhance decision-making, boost meat production processes, as well as guarantee to a large extent food safety with reduced contaminations in meat. AI-powered imaging procedures enable fast and precise meat quality evaluation by assessing several features including meat marbling, colour, and tenderness. Advanced biosensors and spectroscopy tools integrated with AI algorithms have greatly enhanced contamination detection, permitting real-time detection and identification of antibiotic filtrates, microbial pathogens, and spoilage during meat processing. In addition, AI-induced automation and robotics are reforming meat handling, reducing waste, as well as improving worker safety in the meat industry. From the perspective of supply chain supervision, extrapolative analytics and block-chain incorporation together with AI have contributed to the enhancement of traceability, logistics effectiveness, and demand forecasting. Regardless of these advancements in meat processing with AI, challenges including high operation costs, data accessibility, and ethical concerns poses some barriers to the extensive adoption of AI in the meat industry. It is suggested that future investigations should centre on cost-effective AI solutions, enhanced data regularization, as well as the integration of emergent technologies including the Internet of Things (IoT) with block-chain to build a more sustainable as well as transparent meat sector. This review highpoints the transformative role of artificial intelligence in the meat sector as well as give future suggestions for safeguarding quality, efficiency, and safety the production of meat/ meat products.

Keywords: Artificial Intelligence, Machine Learning, Meat Science, Food Safety, Automation, Supply Chain Optimization

Introduction

Meat science encompasses a broad range of disciplines, including meat processing, safety, and quality assurance. The global meat industry is a critical part of the food sector that is saddled with the responsibility of meeting the growing demand for improved-quality and healthy meat and its products. The meat industry is also part of the food sector charged with the mandate to support global food security and food sustainability (Ederer *et al*., 2023). However, due to the high demand of meat necessitated by the astronomic growth in human population in recent years, there seems to be a surge in the production of contaminated and poor quality meat. High-profile foodborne disease outbreaks (Salmonella outbreaks) connected to meats and mince beef, have drawn close media attention as well as raised public consciousness and awareness of the risks linked with the consumption of polluted food (Muthusamy *et al*., 2024). In order to address the increasing worries for public health, food hygiene has become a major priority all over the world, with a keen focus on the prevention of incidences related to pathogen-linked contamination in food (Tropea, 2022).

According to literatures (Parlasca and Qaim, 2024; Wood *et al*., 2024), meat is a main source of animal protein in the diets of most people globally (offering vital macro and micronutrients, as well as important fatty acids). However, it has now become a central emphasis in the discussions of food safety. For instance, the Food and Agriculture Organization and the Organization for Economic Co-operation and Development (OECD) of the United Nations (FAO) have recounted that the consumption of meat over the years has doubled with a predicted 14 % increase by 2030 as a result of the growth in human population (Muthusamy *et al*., 2024). Chicken meat is projected to contribute to 41 % of the aggregate meat protein globally, next to pork (34 %), beef (20%), as well as mutton with 5 % contribution (Muthusamy *et al*., 2024). This predicted surge in meat consumption increases the quest for fast, accurate uncovering of foodborne pathogens to avoid outbreaks and guarantee public health and safety. Likewise, the increasing global demand for meat also calls for the need for innovative methods in the production of meat in order to ensure consistency, safety, and sustainability (Mehdizadeh *et al*., 2025). Traditional methods of meat inspection and quality control rely heavily on manual labour and subjective evaluation, which can lead to variability and inefficiencies in meat quality and safety assessment (Taheri-Garavanda *et al*., 2019). This situation has further highlighted the need for alternative approaches in producing quality and healthier meat for human consumption.

As the world moves more into a digital age, AI-driven solutions is one of the answers to this search because it provides data-driven approaches that improve accuracy, efficiency, and scalability of meat and meat products (Todhunter *et al*., 2024). The role of AI in the production of quality and healthy meat has expanded with advancements in image recognition, predictive analytics, and automated processing systems, enabling a more systematic approach to meat production in terms of quality and safety (Saha *et al*., 2025). Artificial intelligence covers a broad spectrum of technologies, that includes deep Learning (DL), Machine Learning (ML), and computer vision, which have been integrated into various facets of meat production (Waqas *et al*., 2025). For instance, AI-driven computer vision systems are employed to evaluate meat quality attributes such as marbling, colour, and texture, providing rapid and consistent assessments that surpass traditional methods (Rahman *et al*., 2020). Additionally, spectroscopy machines incorporated together with artificial intelligence algorithms enable the uncovering and discovering of harmful chemicals and adulterants in meat, thereby enhancing food safety measures (Ziani *et al*., 2025).

The amalgamation of artificial intelligence extends beyond meat quality assessment and safety, it also plays a crucial part in optimizing the management of supply chain in meat handling. AI-based predictive analytics facilitate demand forecasting, inventory management, and logistics optimization, contributing to reduced waste and improved efficiency in meat distribution (Zatsu *et al*., 2024; Agrawal *et al*., 2025). Furthermore, the incorporation of AI with Internet of Things (IoT) devices and block-chain technology has paved the way for transparent and traceable meat supply chains, ensuring authenticity and building consumer trust in the meat/ meat products that they purchase in the stores (Ellahi *et al*., 2023).

AI currently plays an essential role in the modernization of meat science, projecting the meat sector into a new age of innovation and improvement on product quality, safety and delivery (Kakani *et al*., 2020). Several other known artificial intelligence technologies also presents data-driven answers that enhance decision-making and streamline operations when grading meat (Feng *et al*., 2018). For example, AI-driven spectroscopy and imaging systems are increasingly used to assess meat composition, detect contaminants, and classify meat grades with high precision (Ziani *et al*., 2025). Furthermore, AI-powered robotic systems have been integrated into slaughterhouses and processing plants to improve accuracy, reduce waste, and enhance workplace safety (Hwa and Chuan, 2024; Dhal and Kar, 2025). As AI continues to advance its role in the production of quality and safe meat, it is expected to expand, offering further opportunities for research and industry adoption (Todhunter *et al*., 2024).

Despite the promising advancements, the adoption of AI in the production of quality and safer meat is not without challenges. High implementation costs, the necessity for large and diverse datasets, and concerns regarding data privacy and ethical AI issues are momentous hurdles that requires honesty attention. By effecting proactive procedures and promoting transparency, stakeholders can make use of the profits derived from AI while moderating associated risks. Some ways to address these issues include; frequently assessing and auditing AI models to detect any form of biases. Secondly, data protection standards can be incorporated during the development stage of AI machines to make sure there is compliance as well as safeguard user data.

Future research is imperative to develop cost-effective AI solutions and to explore the incorporation of artificial intelligence with evolving technologies to promote sustainability and resilience in the meat sector. In summary, AI has evolved as an evolutionary approach in the meat sector, offering innovative answers for quality evaluation, safety monitoring, as well as supply chain efficiency and optimization. As the technology continues to evolve, it holds the potential to further revolutionize meat production processes, ensuring they meet the growing demands for efficiency, safety, and sustainability. Figure 1 shows a summary of the role of artificial intelligence in meat quality and safety production. The goal of this review is to summarize in brief from literatures, the role of AI in promoting meat quality and safety in the food industry.

Methods

The Application of Machine Learning (ML) Models

Different kinds of machine learning models and AI algorithms have been used in the production of meat for quality and safety purpose. Table 1 gives a summary of the key applications of AI in the meat quality and safety production, the methodologies used, and the performance metrics achieved. For example, several machine learning models such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes, and Artificial Neural Networks (ANNs) have been used to perform assessment task for meat quality and safety production. These AI algorithms have been used for classification tasks such as meat freshness assessment and carcass characterization. For example, KNN achieved a classification accuracy of 92.59 % in evaluating beef freshness (Arsalane *et al*., 2024; Anwar and Anwar, 2025).

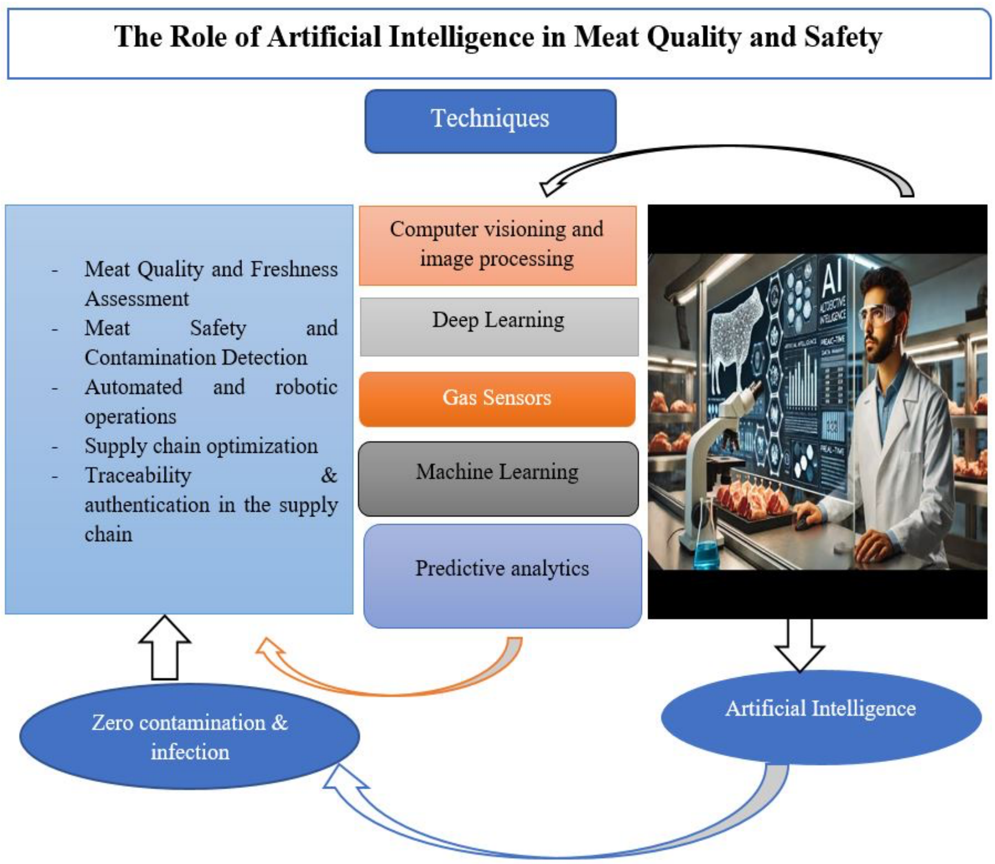

Fig. 1: Applications of AI-Driven Innovations in Meat Quality and Safety

Table 1: Comparison of key role of artificial intelligence in the meat sector

S/N	System Application	Technology/ Methodologies	Performance/ Accuracy
1	Beef Freshness Evaluation	KNN, SVN, Naive Bayes	92.59 %; 90.12%; 87.65%
2	Beef Cutting Classification	Learning Transfer (EfficientNetB0)	99.81%
3	Meat Spoilage Detection	CNN, Gas Sensors	99 %
4	Lamb Carcass Classification	ANN, SVM	0.88; 0.83
5	Prediction of Chicken Meat Freshness	ANN, Computer Vision	Correlation Coefficient: 0.98734

Sources: Taheri-Garavanda *et al*., 2019; Gc *et al*., 2021; Arsalane *et al*., 2024; Bhuiyan *et al*., 2024; Anwar and Anwar, 2025; Liu *et al*., 2025; Mjahad *et al*., 2025; Ziani *et al*., 2025)

Convolutional Neural Networks (CNNs) and Deep Learning (DL) in Meat Classification

The use of deep learning methods, mostly Convolutional Neutral Networks (CNNs), have been widely adopted for image-based classification tasks in the production of meat. For instance, transfer learning models such as EfficientNetB0 and VGG16 have been used to classify beef cuts with high accuracy, achieving up to 99.81% accuracy (Gc *et al*., 2021).

Computer Vision and Image Processing for Assessing Meat Quality

Computer vision in the meat industry has been widely employed for quality evaluation of meat (non-destructive quality). Techniques such as image processing and feature extraction have been employed to assess meat quality parameters such as color and texture (Liu *et al*., 2025; Mjahad *et al*., 2025). For example, a study used computer vision and ANN to predict chicken meat freshness with a statistical correlation coefficient of 0.98734 which is a very acceptable value for meat quality (Taheri-Garavanda *et al.,* 2019).

Gas Sensors and Internet of Things (IoT) Integration

Gas sensors have been integrated with AI models to detect spoilage in meat. For example, a system combining gas sensors and deep learning algorithms achieved a classification precision of 99% in detecting meat freshness and species classification (Bhuiyan *et al*., 2024).

This table highlights the key applications of AI in the meat quality and safety production, the methodologies used, and the performance metrics achieved. Where: KNN = K-nearest neighbor; SVN = Support Vector Machine; CNN = Convolutional Neural Network; ANN = Artificial Neural Network.

The Role of AI in Promoting the Production of Quality and Safety Meat

Meat Quality and Freshness Assessment

AI has played a crucial role in detecting meat spoilage and monitoring freshness. Techniques such as gas sensors, image processing, and neural networks have been integrated to classify meat spoilage levels. For example, a system combining gas sensors and image processing achieved an accuracy of 82 % in classifying spoiled meat levels (Kartika *et al*., 2018). Additionally, deep learning simulations have been utilized to classify meat freshness with the use of image data, achieving a classification accuracy of 99 % (Bhuiyan *et al*., 2024).

Artificial intelligence has significantly enhanced the accuracy and efficiency of various tasks in meat sector, demonstrating its potential for future applications. AI has enhanced the evaluation of meat characteristics such as marbling, tenderness, colour, and water-holding capacity. Machine learning models conditioned for large datasets can predict meat quality parameters more accurately than traditional methods (Feng *et al*., 2018). Computer vision systems analyse images of meat cuts to classify them based on quality grades, reducing subjectivity and human errors (Taheri-Garavanda *et al*., 2019).

Meat Safety and Contamination Detection

In order to allay all forms of fear with regards to consumers acceptability, it is important to ensure meat safety and efficiently detect any form of contamination in meat which is a serious aspect of public health protection and safety. For decades, the traditional approach of detecting contaminants in meat have been very time – consuming and labour-intensive while in most cases, it requires broad laboratory scrutiny. However, with the advent of AI, this process has been revolutionized by the introduction of fast, precise, as well as non-invasive approach. This section of the present manuscript explores the AI-driven techniques used in achieving meat safety and detection of contamination in meat and its products preventing the risk of pathogen infection in consumers via the route of contaminated meat. Literatures has shown that AI-powered biosensors and deep learning models can be adopted to detect/identify microbial infection and contamination, antibiotic residues, and spoilage in meat products (Mehdizadeh *et al*., 2025; Ziani *et al*., 2025). Spectroscopy combined with AI algorithms allows real-time and precise detection of disease causing (pathogens) organisms such as *Escherichia coli* and Salmonella, ensuring safer meat products (Ziani *et al*., 2025).

The use of spectroscopy-based devices integrated with AI codes is a powerful instrument for detecting meat contamination and adulteration. A practical illustration is the Fourier Transform Infrared (FT-IR) spectroscopy that can be used to detect biochemical compromise in meat, enabling a fast discovery of microbial spoilage (Muthusamy *et al*., 2024). Study show that, FT-IR has successfully been employed to measure changes in meat by providing a metabolic picture that allows for the quantification of microbial burdens directly from the surface of meat (chicken) within few seconds (Muthusamy *et al*., 2024). The use of Near-Infrared Spectroscopy (NIRS) incorporated with AI codes has further been utilized to evaluate meat quality and safety (Zheng *et al*., 2023; Fodor *et al*., 2024; Sarker *et al*., 2024).

Another method of accelerated means of detecting pathogenic contamination in meat is through the use of optical imaging techniques incorporated with AI codes. AI algorithms has been reported to analyse optical images for the identification of bacterial loads at the micro-colony stage, significantly reducing detection time (Ma *et al*., 2023; Yang *et al.,* 2023). A research study reported that this approach of meat screening could detect micro-organisms within few hours of inoculation, thereby jettisoning the need for the known prolonged traditional methods of detecting meat contamination (Salama and Chennaoui, 2022).

Conversely, the use of hyperspectral imaging, promoted by AI, offers another method of detecting foreign materials and contaminants in meat. By gathering data across different wavelengths, this method can detect all forms of anomalies that are invisible to the natural eye. Recent studies have applied the use of hyperspectral imaging to identify foreign materials in meat, demonstrating its usefulness in enhancing food safety protocols (Campos *et al*., 2023; Payne *et al*., 2023; Kucha and Olaniyi, 2024).

Automated and Robotic Operations in Meat Processing

AI-driven robotics are transforming meat processing by automating slaughtering, deboning, and packaging operations. Robotics integrated with AI enhances precision, reduces waste, and improves worker safety in meat processing plants (Hwa and Chuan, 2024; Dhal and Kar, 2025). For instance, during slaughtering in abattoirs, AI- driven robotic operations have been employed to carry out slaughtering tasks with increased speed, precision and consistency (Hassoun *et al*., 2023). These kind of systems make use of well-developed sensors and control codes (algorithms) to handle livestock in a humane manner efficiently. For example, robots that are conditioned with vision systems can recognize anatomical benchmarks to accomplish accurate cuts, plummeting stress on livestock as well as improve meat quality after cuts (Khodabandehloo, 2022; Kim *et al*., 2023). Conversely, challenges exist in adapting to different livestock sizes and anatomies, which in turn can hinder the precision of robotic operations during slaughtering of animals (Purnell and Gifhe, 2013).

Secondly, during deboning and cutting of livestock parts which ordinarily is a labour-intensive processes that needs precision to maximize yield and guarantee meat quality, the use of robotic system can be employed. Research have shown that the use of robotic machines that are equipped with imaging devices (such as 3D vision systems), can evaluate the shape and size of each carcass to execute customized meat cuts during slaughtering (Esper *et al*., 2021). These robotic systems improve precision and lessen meat waste. A practical example, is the use of the Meat Factory Cell (MFC) concept to integrate robotics and intelligent concepts that will perform deboning tasks, which demonstrates the prospect for increased automation during meat processing (Mason *et al*., 2024).

Furthermore, the use of automation during packaging of meat can be achieved with the use of robotic arms as well as conveyor devices to sort, package, as well as label meat products before they are transported for sale (Kim *et al*., 2023). These automated technology can handle different packaging setups and sizes, thereby increasing throughput and lessening labour costs (Kim *et al*., 2023). In addition, the use of automated packaging devices boost hygiene by reducing human contact with meat and its products. The implementation of this kind of state of the art technologies has been shown to improve the general efficiency in meat processing facilities (Kim *et al*., 2023; Mason *et al*., 2024).

Supply Chain Optimization of Meat During Production

AI-based predictive analytics optimize meat production and distribution by forecasting demand, minimizing food waste, and improving logistics. Smart sensors and block-chain technology, when combined with AI, enable real-time tracking of meat from farm to consumer, enhancing transparency and traceability (Ellahi *et al*., 2023). AI has enabled automation in meat processing, improving production efficiency and product consistency. For instance, AI-based systems have been developed to classify carcasses automatically, plummeting the necessity for manual inspection. According to García-Infante *et al*. (2024), it was demonstrated that machine learning algorithms such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) classified lamb carcasses with high accuracy, achieving overall accuracies of 0.88 and 0.83, respectively.

Traceability and Authentication of Meat in the Supply Chain

AI has also been used to enhance traceability and validation of product in the supply chain of meat processing and packaging (Khan *et al*., 2022). Machine learning algorithms is utilized to classify meat products based on their origin and production systems (Mustapha *et al*., 2024). For example, a study used ML algorithms to differentiate between lamb production systems, achieving high classification accuracies (García-Infante *et al*., 2024). This ensures that meat eaters (consumers) can trust the source as well as the quality of meat that they purchase from the stores.

Emerging Roles of AI in Cultivated Meat

AI is also being explored in the production of cultivated meat, a sustainable alternative to traditional animal farming. Machine learning techniques are being used to optimize the bio-printing process, predict printability, and characterize meat quality. For instance, Machine Learning (ML) can help in modeling sensory characteristics and confirming the cultured meat repeats the preferred flavour and texture (Barbosa *et al*., 2023; Ng and Tan, 2024).

Challenges and Future Perspectives

Despite its benefits, AI adoption in the meat industry faces obvious obstacles including the need for large datasets, high operational costs, and concerns regarding ethical AI usage. Research work in the future should centre on developing cost-effective artificial intelligence solutions and incorporating AI with evolving technologies including the Internet of Things (IoT) and blockchain to improve meat industry sustainability (Dhal and Kar, 2025). Furthermore, there is a need to do research in areas such as real-time monitoring systems and autonomous robotic systems for automation (Shi *et al*., 2021; Alvarez-García *et al*., 2024).

Conclusion

Artificial intelligence is reshaping the process of cultivating meat production by enhancing quality assessment, safety monitoring, automation, and supply chain efficiency. While challenges remain in this new area of research, ongoing investigation and technological advancements will further drive AI's impact in meat processing, ensuring a more efficient and sustainable meat industry. The integration of machine learning, deep learning, computer vision, and IoT has enhanced the accuracy, efficiency, and sustainability of meat production and distribution. As AI technology develops over the years, its applications in meat industry are expected to expand, addressing current challenges and enhancing the overall quality as well as safety of meat for consumers acceptability and welfare.

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