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Review

The Role of Artificial Intelligence in Meat Production and Processing

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Abstract

The use of Artificial Intelligence (AI) in meat production and processing has significantly transformed the meat industry. AI has enhanced the efficiency, sustainability, animal welfare, and food safety. AI is increasingly transforming the agricultural and food production sectors, with a significant impact on meat production and processing. AI technologies are being integrated into various stages of meat production, from livestock management and health monitoring to supply chain optimization and meat processing. The multifaceted role of AI across the meat production supply chain—from livestock farming, production, processing, packaging, and distribution is investigated in this article. This review paper critically analyzes current applications, benefits, challenges, and future potential, emphasizing AI's capacity to meet the rising global demand for meat while addressing environmental and ethical concerns. AI is a transformative force in livestock management, offering unprecedented capabilities in health monitoring, feeding, breeding, and welfare assessment. AI is redefining the processing, packaging, labeling, quality control, distribution, and regulatory compliance steps in the meat industry. With tools like computer vision, predictive analytics, and robotic automation, meat producers can achieve greater accuracy, traceability, and efficiency. AI also provides a more robust and reliable foundation for protecting public health through sustainability and waste reduction in meat production.

Keywords: Carcass, Industry, Machine Learning, Robots, Vision.

Introduction

Meat and meat products were one of the main foodstuffs in human nutrition worldwide for centuries. Meat comprises proteins, vitamins, dietary fats, and other essential nutrients. It is a crucial and fundamental component of human beings' daily diet (Grujic, 2010). The global meat industry is important constituent of modern food systems (Mohammad, 2016). This industry is under increasing pressure to meet rising consumer demands, production of hygienic meat, ensure food safety, reduce environmental pollution, and maintain operational efficiency. Traditional meat production methods are often labor-intensive, prone to inefficiencies, and difficult to scale. With the introduction of AI, producers can now rely on data-driven decision-making, smart automation, and predictive analytics to streamline operations and ensure consistent product quality. Artificial Intelligence (AI) is rapidly emerging as a transformative force that addresses many of these challenges. From precision livestock monitoring to robotic butchering and automated quality checks, AI is redefining meat production in profound ways.

Challenges in traditional meat inspection include, inconsistent evaluations due to human error or fatigue, Labor shortages in processing facilities, Difficulty detecting micro-contaminants or subtle quality deviations, Pressure to maintain line speed while ensuring accuracy. Computer vision addresses these issues by combining high-resolution imaging with AI algorithms that detect, classify, and quantify various quality parameters in real time.

Through the use of AI Modern processing facilities integrate computer vision systems directly into production lines. This enables: real-time feedback loops to divert substandard products, automated sorting and trimming of carcasses based on quality and integration with robotics for physical product manipulation. AI systems such as Tecnoincar (2023) and Vimaan Robotics (2024) are used in high-speed facilities under USDA regulation to inspect packaging labels, detect seal integrity, and confirm barcode compliance. AI based systems also can detect materials such as: Metal, plastic, and bone fragments, Hair, fecal matter, and dirt, Insects and parasites. Kim & Lee (2024) used hyperspectral imaging to detect contaminants on pork bellies with high sensitivity using a 245-band scanner paired with an ensemble deep learning model.

Training of AI systems is essential for their proper functioning. AI models are trained using: thousands of annotated images representing defects and normal conditions, data augmentation techniques (e.g., rotation, zoom, color shift) to improve model generalizability and active learning frameworks to improve performance with minimal manual input (Carver *et al*., 2021, Subramaniam *et al*., 2022). Despite many advantages of using AI systems and technologies for meat production and processing, it involves certain disadvantages also such as high initial investment in hardware and integration, data drift due to changes in lighting or meat characteristics, limited regulatory acceptance of AI-based grading and inspection (Sharma *et al*., 2021).

This Article aims to explore how AI technologies are applied across different stages of meat production. Impact of AI on labor, sustainability, ethics, and food security are also described. This also provides a framework for future AI adoption in the meat industry.

Technological Foundations of AI in Meat Production and Processing

Artificial Intelligence (AI) has become an essential component in modern meat processing systems, driving automation, precision, and efficiency. This chapter explores the technological infrastructure that supports the deployment of AI across the meat supply chain. These foundations include machine learning, computer vision, robotics, sensor technologies, data analytics, and cloud computing—each of which plays a unique role in optimizing meat production (Barbut, 2020; Liu *et al*. 2021).

1. Machine Learning (ML)

Machine learning algorithms are at the core of AI systems in meat processing. ML enables machines to learn from data, identify patterns, and make decisions without explicit programming. Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) have been used to classify meat quality based on image data (Kamani *et al*., 2021). In meat production, other application of ML include:

- **Animal behavior analysis**: Detecting stress or illness based on movement or feeding patterns.
- **Yield prediction**: Using historical processing data to forecast output and optimize cutting techniques.

- **Defect classification**: Training models to recognize abnormalities in meat products.

2. Computer Vision

Computer vision enables machines to interpret visual information from cameras and sensors. Computer vision systems allow for real-time inspection that is faster and more consistent than manual methods. In meat processing, this technology is critical for - grading carcasses, measuring marbling and fat content, detecting contaminants and foreign objects and automating cutting and sorting processes.

Technical components of computer vision technology are High-resolution cameras, deep learning algorithms (e.g., YOLO, ResNet) and spectral imaging (e.g., hyperspectral or multispectral) (Meunier et al., 2020; Fiore et al., 2020).

3. Robotics and Automation

Robotics in meat processing involves the use of intelligent machines to carry out repetitive, dangerous, or high-precision tasks. Robots integrated with AI and sensor technology can perform high-speed deboning, Handle meat delicately to avoid product damage and adapt to anatomical variations in carcasses (Jagtap et al.2020; Jin et al., 2020). Dr. Basem Adel Aly developed a knife-wielding robot capable of mimicking human butchery techniques using AI-driven sensory feedback (Aly, 2024). Due to their capacity to boost output, lower labor costs, and enhance biosecurity protocols, robots are gaining popularity in the food industry (Morstatter, 2023; Nilsson, 2009; Samad et al.2022).

4. Sensor Technologies

Sensors serve as the interface between physical operations and AI systems. They collect critical data, including - Temperature, pH, and humidity (environmental and carcass-specific), Weight and dimensions (for portioning and sorting) and Motion and proximity (for robotic navigation and interaction). These sensors are often integrated with edge computing platforms, allowing immediate processing of the data they generate.

Application of AI in Meat Production and Processing

1. Application of AI in Livestock Management and Health Monitoring

Livestock management is a critical phase in the meat production supply chain. It encompasses animal welfare, health monitoring, feed optimization, breeding, and environmental control. Traditionally, these tasks have relied heavily on manual labor and subjective assessment. However, the integration of Artificial Intelligence (AI) has transformed livestock farming into a data-driven, automated system that improves efficiency, animal welfare, and economic returns.

i. Precision Livestock Farming (PLF) and AI

Precision Livestock Farming (PLF) involves using advanced technologies to monitor individual animals and their environment. AI enhances PLF by analyzing large datasets from sensors, cameras, and biological inputs to detect early signs of disease by monitoring the behavior and activity levels of animals. This technology also helps in optimize feed and water consumption and also track reproductive cycles and calving. Common AI techniques Used under the precision livestock farming are - Machine learning for pattern recognition, Time-series analysis for detecting anomalies and Reinforcement learning for adaptive feeding systems (Ezanno et al., 2021; Viejo et al., 2022).

Animal health is a top priority in livestock farming. AI systems are now capable of detecting illness before it becomes visibly apparent. These systems use: Computer vision to analyze gait, posture, and facial expressions for signs of lameness or discomfort. Acoustic monitoring to detect respiratory conditions from cough patterns and wearable sensors to track temperature, movement, and heart rate. InFarm's AI-based cattle monitoring system in Queensland utilizes camera analytics and machine learning to assess animal condition, stress, and movement in real time (InFarm, 2023). Computer vision systems analyze cattle movement to detect abnormal patterns that may suggest lameness, heat stress, or injury (Kang et al., 2021).

AI helps optimize breeding programs by analyzing -Genetic data for desirable traits, Hormonal and behavioral signals indicating estrus and calving patterns to predict labor needs and complications. Companies like Connecterra

and Cainthus are using AI to monitor estrus cycles and fertility windows, enhancing reproductive success rates in dairy and beef herds (Wile, 2021).

AI models can analyze feed intake patterns and recommend adjustments to maximize growth while minimizing waste. Some systems use reinforcement learning to develop adaptive feeding schedules based on growth rate, weather conditions and feed conversion efficiency. This not only improves productivity but also reduces environmental impact by lowering methane emissions per unit of meat produced.

Under the automated systems of precision livestock farming, sensors and AI systems can automatically regulate - Barn temperature and humidity, Airflow and ammonia levels, Lighting cycles to mimic natural conditions. Smart environments help reduce stress and disease, thereby enhancing overall productivity.

The value of AI in livestock farming is magnified when multiple data streams are integrated. Platforms using cloud computing and edge AI aggregate - sensor data, veterinary records, genetic profiles. Farmers receive alerts and actionable recommendations via mobile dashboards, enabling informed and timely decisions. Despite its benefits, several challenges limit the widespread use of AI in livestock management. The major limitations are - high implementation and maintenance costs, need for training and education among farmers, concerns over excessive surveillance and animal autonomy. Ethical AI use requires transparency, stakeholder involvement, and compliance with animal welfare standards.

2. Quality Assurance in Meat Inspection

The quality and safety of meat products are fundamental to consumer health, regulatory compliance, and brand integrity. Traditionally, meat inspection relies on visual assessments performed by trained human inspectors. However, this approach can be subjective, inconsistent, and labor-intensive. Most of the AI-based methods are non-destructive and involves minimum human interference (Chen et al., 2013). Al-Sarayreh *et al*., (2018) utilized the spectral technology, and Li *et al*., (2016) utilized the sensor technology to assess the quality of meat. Computer vision, powered by artificial intelligence (AI), is transforming quality assurance in meat production through rapid, objective, and scalable inspection methods (Sun et al., 2016). This chapter explores how computer vision technologies are being used to enhance meat inspection and ensure high standards of product quality and safety.

Computer vision involves the capture and analysis of image data to interpret features like color, shape, texture, and structure. In meat inspection, this includes:

- **RGB cameras** for color and appearance analysis.
- **Infrared and thermal cameras** to assess temperature differentials.
- **Hyperspectral imaging (HSI)** for chemical composition and contaminant detection.

These systems are trained on large datasets and leverage deep learning models—such as convolutional neural networks (CNNs)—to identify patterns indicative of quality or safety issues.

Emerging trends in computer vision for meat inspection include: 3D imaging for volumetric analysis and robotic cutting, self-learning AI models that adapt to facility-specific characteristics, multi-modal systems that combine vision with olfactory and biosensor data, and augmented reality (AR) tools to assist human inspectors with overlays and alerts.

These innovations will further embed AI in quality assurance workflows and elevate food safety standards globally. Grading of carcass (meat) based on marbling (intramuscular fat), color, and muscle shape is crucial for determining market value. Computer vision systems analyze cross-sectional images of meat cuts and quantify marbling scores according to USDA or equivalent standards. Changes in color and texture can indicate spoilage or microbial activity. Vision systems are trained to detect: Browning or discoloration, Surface dryness or slime and abnormal muscle texture. These attributes are often imperceptible to the human eye but are detected through image analysis at the pixel level. Major advantages of using AI systems for quality assurance at the production line include high speed, consistency, traceability and scalability

Regulatory bodies such as the USDA and EFSA are beginning to recognize AI tools in meat inspection, but

widespread adoption requires: validation of AI accuracy vs. human inspection, Transparent documentation of inspection algorithms and Secure data handling practices. Ethical use also includes ensuring that automation does not displace workers without providing reskilling opportunities.

3. AI in Packaging, Labeling, Traceability, and Distribution of Meat and Meat Products

In the final stages of the meat production supply chain—packaging, labeling, and distribution ensure that meat products reach consumers safely, compliantly, and efficiently. With increasing demand for transparency, efficiency, and food safety, artificial intelligence (AI) has emerged as a vital enabler of automation and optimization across these operations. This section explores the role of AI in streamlining packaging, verifying labels, and enhancing logistics in meat production systems. Packaging is essential not only for presentation but also for product protection, shelf life extension, and regulatory compliance. AI is applied in smart packaging systems to Monitor packaging integrity using computer vision, predict spoilage with machine learning models analyzing sensor data and Adjust packaging processes in real time based on line performance. AI-powered inspection systems use high-speed cameras and neural networks to detect sealing defects, labeling errors, and contamination inside the package, all in real time (Tecnoincar, 2023).

Accurate labeling is critical to ensure compliance with local and international regulations, including nutritional facts, expiration dates, allergens, traceability codes, and country-of-origin information. Different AI-based systems are enabled for optical character recognition (OCR) to verify printed text and barcodes, Computer vision to detect misaligned or incorrect labels and Natural language processing (NLP) to validate label content against product data. Vimaan Robotics (2024) integrates OCR and AI classification to inspect over 1,000 packages per minute in USDA-regulated plants, ensuring 88.8% label accuracy.

Consumers and regulators increasingly demand full traceability from farm to fork. AI plays a central role in: Linking product data (origin, processing history, batch number) through intelligent tracking systems, automating event logging across the supply chain using IoT and cloud platforms and enhancing blockchain-based ledgers to ensure immutable, real-time updates (Defraeye *et al*., 2021; Liu et al 2021). IBM Food Trust, in collaboration with meat processors, uses AI to integrate traceability data into blockchain systems, reducing recall response time from days to seconds (IBM, 2023).

Distribution logistics in meat production are complex due to perishability, strict temperature control, and regional regulations. AI enhances logistics in the following ways: Predictive analytics for real-time traffic/weather for smooth transfer of goods, Sensor data analysis with alert systems for temperature and humidity fluctuations during transport, inventory management through demand forecasting and Vision-based validation of loading/unloading. Companies like JBS and Tyson Foods leverage AI to dynamically route trucks based on real-time temperature data and customer demand forecasts (Wile, 2022).

4. Ensuring Meat Safety and Compliance with Quality Control Measures through AI

Food safety is a non-negotiable priority in meat production, with global regulatory frameworks designed to prevent contamination, ensure traceability, and protect consumer health. Traditional food safety systems rely on manual inspections, batch testing, and human-led compliance auditing—approaches that are reactive and prone to delay. Artificial Intelligence (AI) introduces a paradigm shift by enabling proactive, real-time food safety monitoring and regulatory compliance enforcement. This chapter explores the applications, benefits, and challenges of using AI to ensure food safety in meat production.

AI enables predictive analytics using machine learning models trained on historical and real-time data to forecast contamination risk and non-compliance events. Supervised learning to classify contamination risk based on facility data (temperature, humidity, handling times). Time-series models (e.g., LSTM networks) to detect deviations in hygiene routines or environmental patterns. Anomaly detection to identify equipment failure or sanitation lapses, Zhang et al. (2023) developed a model that predicted *Listeria* contamination events in meat plants with over 75% accuracy based on sensor and process data. Emerging directions in AI-driven food safety include: Multimodal AI systems combining vision, scent detection, and microbiome analysis, Self-learning AI that continuously adapts to changing facility conditions, Regulatory AI assistants that automatically update SOPs based on changing laws and AI-enabled digital twins of processing plants for food safety simulation and training.

AI-powered computer vision systems are being deployed to visually monitor- surface cleanliness of equipment and carcasses, worker hygiene compliance (e.g., glove use, handwashing), Foreign object detection (e.g., plastic, metal, insects). These systems operate at high speed and precision, greatly surpassing human observation capabilities. Algorithms are trained on thousands of labeled images to identify non-conforming visual patterns. Through the use of IoT sensors and edge computing, AI systems can continuously monitor critical control points (CCPs) in the processing chain and trigger real-time alerts when deviations occur. AI tools are used to ensure continuous compliance with food safety regulations such as: HACCP and FSSA

AI also improves food traceability through-Integration with blockchain platforms for secure, transparent supply chain records, use of computer vision and barcode/RFID scanning to match product batches with facility and transport data (Marvin et al., 2022). AI-assisted recall simulations to estimate the scale and impact of hypothetical contamination events. When a contamination alert is issued, AI systems can rapidly trace the affected product through the supply chain, minimizing recall time and cost (IBM, 2023). Tyson Foods implemented an AI-driven food safety platform that combines sensor data, environmental controls, and predictive modeling. According to Wile (2022), the system reduced contamination-related shutdowns by 40% in the first year and enhanced its compliance reporting capability by automating document audits across multiple facilities.

5. Sustainability and Waste Reduction in Meat Industry by Using AI

The meat industry is increasingly turning to Artificial Intelligence (AI) to optimize resource use, reduce environmental burdens, and create circular production models. Meat production presents several environmental challenges, including methane emissions from livestock, High energy and water consumption in processing, Waste generation, including bones, fats, offal, and spoiled meat and Land degradation from intensive livestock farming.

AI helps optimize the use of energy, water, and raw materials across the meat supply chain. Smart sensors paired with AI detect leaks, optimize cooling systems, and minimize wash cycles in processing plants. Machine learning algorithms forecast peak energy demands and shift operations accordingly to reduce emissions and costs. Real-time monitoring ensures that resources like water and chemicals are not overused in sanitation processes. Cargill implemented AI-enabled energy management systems in several meat plants and reduced electricity consumption by 12% over 17 months (Cargill, 2023). AI also helps to identify potential secondary uses for meat byproducts (e.g., pet food, biofuels, collagen supplements). The European firm VION uses AI-driven rendering optimization to extract 7% more usable product from animal byproducts than standard processing lines (VION, 2022).

AI platforms now integrate emissions data from across the supply chain to calculate real-time carbon footprints for specific products or batches. Life Cycle Assessment (LCA) models enhanced with AI to evaluate energy, water, and emissions inputs. Digital twins of production systems to simulate and test environmental interventions. Blockchain-integrated carbon tracking to ensure emissions data transparency. Such systems enable meat producers to target interventions, participate in carbon credit markets, and meet ESG (Environmental, Social, Governance) requirements.

Challenges, Ethics, and Policy Implications for the Application of AI in Meat Industry

While Artificial Intelligence (AI) offers vast potential to transform meat production through improved efficiency, sustainability, and safety, its adoption also raises critical challenges. These range from technical limitations and workforce disruption to ethical concerns and regulatory uncertainties. As AI becomes more integrated into the meat industry, it is essential to address these issues to ensure responsible and equitable implementation.

Challenges

AI systems depend on large volumes of high-quality data. In meat production, data collection may be hampered by: Lack of digitization in older facilities, Fragmented data sources across production, inspection, and distribution and Sensor failures or inconsistencies in real-time monitoring systems. Without standardized and clean data, AI models can produce inaccurate or biased outputs (Dey et al., 2022). Many meat processing operations lack the necessary IT infrastructure to support AI. AI models, especially deep learning systems, are often considered "black boxes." This lack of explainability can create trust issues.

Ethical Concerns

Automation through AI can lead to labor displacement and workforce impact by Job displacement in roles such as inspection, packaging, and logistics, Deskilling of workers as decision-making is shifted to machines, Widening inequality, particularly in low-income rural regions where meat processing jobs are concentrated. Solutions require inclusive policies for retraining, education, and worker engagement (Brynjolfsson & McAfee, 2020).

Regulatory Challenges

Existing food safety and labor regulations were not designed with AI in mind. Key regulatory gaps include: Accountability for AI decisions: Who is liable when AI systems fail? Approval processes: How should AI inspection systems be certified? Cross-border standards: What happens when AI tools approved in one country are deployed in another? Governments and international bodies must develop new frameworks to govern AI in food production (FAO, 2023).

Adoption of AI should include: Consultation with workers, farmers, regulators, and consumers, Ethical review boards in major corporations, and Transparent reporting of AI system performance and impacts.

Table 1: Major applications of AI in different facets of Meat industry

Application Area	AI Role/Impact	Reference
Demand & Price Forecasting	Predicts demand, optimizes pricing, manages inventory	Nguyen, (2023); Nassibi *et al*., (2023)
Cold Chain & Quality Control	Monitors temperature, ensures hygiene and freshness	Li *et al*., (2023)
Product Innovation	Replicates meat texture/flavor, optimizes blends	Pierre *et al*., (2024)
Automated Processing	Precision cutting, quality inspection, defect detection	Delmore, (2022); Barbut, (2020)
Cultured Meat	Streamlines experiments, predicts optimal conditions	Todhunter *et al*., (2024)
Supply Chain Optimization	Tracks products, optimizes logistics, reduces waste	Culot *et al*., (2024); Wang and Li (2024)
Food Safety	Detects contaminants/pathogens in real-time	Suthar *et al*., (2024); Naseem and Rizwan, (2025).

Conclusions

AI is rapidly reshaping the meat production landscape, from farm to fork. By integrating advanced analytics, automation, and machine learning, companies are achieving greater efficiency, product quality, safety, and sustainability. The technological foundation of AI in meat processing is a complex ecosystem involving intelligent software, sophisticated hardware, and integrated data systems. These technologies are reshaping the meat industry by improving precision, reducing waste, and enhancing overall product quality. As these systems evolve, continued investment in infrastructure, talent, and research will be critical for scalable adoption. The future of AI in meat production is rich with innovation. From autonomous ranches and digital twins to lab-grown meat and personalized nutrition, AI will continue to evolve the sector far beyond current capabilities. However, these opportunities must be pursued with attention to ethics, inclusivity, and sustainability. The next decade will likely see AI not just as a tool for efficiency, but as a foundational component in reshaping how meat is produced, consumed, and understood. While AI offers transformative benefits for meat production, its adoption must be approached with care. Ethical, technical, and policy challenges must be addressed through proactive governance, inclusive design, and responsible regulation. A collaborative approach—bringing together industry, government, academia, and civil society—is essential to ensure AI supports a food system that is not only efficient, but also fair, ethical, and sustainable.

Contribution by Authors

All the authors contributed equally to writing the manuscript. The final manuscript was read by all authors and consented to publication.

Conflict of Interests

There is no conflict of interest.

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