Meat Research
Vol 6, Issue 2: 1-7, Article 138, April, 2026
ISSN: 2790-1971
https://doi.org/10.55002/mr.6.2.138 http://www.bmsa.info/meatresearch

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Keywords:
Artificial intelligence
Animal by-products
Meat-processing waste
Waste valorization
Resource recovery
Circular bioeconomy

Article Info:
Received: 08 March 2026
Accepted: 09 April 2026
Published online: 30 April 2026

Review Article

AI-based technologies for converting animal meat-processing wastes into value-added products: A comprehensive review

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Abstract

Meat processing industries generate substantial quantities of animal by-products and residues, including blood, bones, fat, skin, feathers, offal, and wastewater. When poorly managed, these materials can contribute to odour, water and soil pollution, greenhouse-gas emissions, and public-health risks. At the same time, their protein, lipid, mineral, and collagen content provide opportunities for resource recovery. This review examines established routes for converting meat-processing wastes into value-added products and evaluates how artificial intelligence (AI) may improve their management and conversion. Potential products include biogas, biodiesel, animal-feed ingredients, compost and biofertilizers, biochar, collagen, gelatin, and protein hydrolysates. The review considers machine learning, deep learning, computer vision, the Internet of Things (IoT), robotics, and predictive analytics in waste classification, process monitoring, yield prediction, and quality control. It also discusses anaerobic digestion, composting, thermochemical conversion, protein recovery, and emerging fermentation approaches, together with their environmental and economic implications. The available literature indicates that AI can support process optimization and decision-making; however, direct applications to meat-processing waste streams remain less developed than applications to general organic-waste management and meat-quality assessment. Data availability, sensor reliability, investment costs, technical capacity, and regulatory requirements remain important barriers. Further pilot- and industrial-scale validation, life-cycle assessment, and techno-economic analysis are needed before the wider benefits of AI-enabled meat-waste valorization can be established.

Introduction

Meat-processing and slaughterhouse operations generate a diverse range of by-products, including blood, bones, fat, skin, feathers, heads, feet, intestinal contents, and wastewater. The quantity and composition of these materials vary with animal species, processing practices, and the degree of recovery already undertaken. Although some by-products are used in rendering and other established industries, poorly managed residues can impose environmental and public-health burdens. Disposal-oriented approaches may also overlook materials containing recoverable proteins, lipids, minerals, and structural biomolecules. Jayathilakan et al. (2012) and Toldrá et al. (2019) describe the potential for recovering useful compounds from meat and animal-processing by-products, while Nizami et al. (2023) place such recovery within the broader concept of waste biorefineries and the circular bioeconomy. Lots of AI driven research has been done to detect meat quality (Hashem et al., 2022, 2023, 2024a and 2024b) but only a few research was found where AI was applied in slaughter waste management (Nizami et al., 2024).

Uncontrolled storage or decomposition of organic residues can contribute to odor, high organic loads in wastewater, nutrient losses, pathogen dissemination, and emissions. The environmental significance of a particular waste stream depends on its composition, handling, and treatment pathway. Valorization can reduce the quantity requiring disposal while recovering energy, nutrients, and materials, but the preferred route must be selected according to feedstock characteristics, product safety requirements, local infrastructure, and market demand. Salemdeeb et al. (2024) emphasize the importance of evaluating the environmental performance of alternative waste-valorization pathways rather than assuming that every recovery option is inherently beneficial.

Artificial intelligence (AI) offers tools for analyzing process data, identifying patterns, predicting outcomes, and supporting operational decisions. Machine-learning methods can be used to estimate biogas yield, assess compost maturity, or relate feedstock properties and operating conditions to product quality. Deep-learning methods extend these capabilities to complex data, including images and sensor streams (LeCun et al., 2015; Goodfellow et al., 2016). In practice, the reliability of such models depends on representative datasets, appropriate validation, and the range of conditions under which they are applied. The Internet of Things (IoT) connects sensors and equipment to systems that collect and transmit process data. When combined with AI, sensor information on temperature, pH, moisture, oxygen, gas composition, and other operating variables can support process monitoring, anomaly detection, and predictive maintenance (Wolfert et al., 2017; Verdouw et al., 2021). Computer vision and robotics may also assist with the identification, segregation, and handling of different by-product streams.

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These capabilities are relevant to meat-processing facilities, although their performance must be validated under practical conditions involving variable feedstocks, wet surfaces, mixed materials, and strict hygiene requirements. A range of conversion pathways is available for animal by-products. Lipid-rich fractions can be processed into biodiesel; protein-rich streams can be rendered, hydrolyzed, or fractionated; and biodegradable residues can be treated through anaerobic digestion or composting. Bones and other mineral-rich materials may also be processed into mineral products or carbonaceous materials. AI may support these processes by predicting yields, optimizing operating conditions, and monitoring product quality. Nevertheless, the evidence base is uneven: many AI applications reported for organic-waste treatment are not specific to slaughterhouse residues, and some proposed applications remain at the modelling or laboratory stage. Against this background, this review (i) outlines the main categories and characteristics of meat-processing wastes; (ii) summarizes conventional routes for their conversion into value-added products; (iii) examines the potential roles of machine learning, deep learning, computer vision, IoT, robotics, and predictive analytics; (iv) discusses biological, thermochemical, and protein-recovery pathways; and (v) identifies environmental, economic, technical, and regulatory challenges and research priorities.

AI-based technologies and their roles in meat-waste valorization

AI and related digital technologies can support several stages of meat-waste valorization, from identifying and separating incoming materials to monitoring conversion processes and assessing final-product quality. Their role is generally enabling rather than replacing the underlying biological, chemical, or thermal conversion processes are shown in Figure 1. The following sections distinguish established waste-treatment pathways from AI functions that may improve their performance.

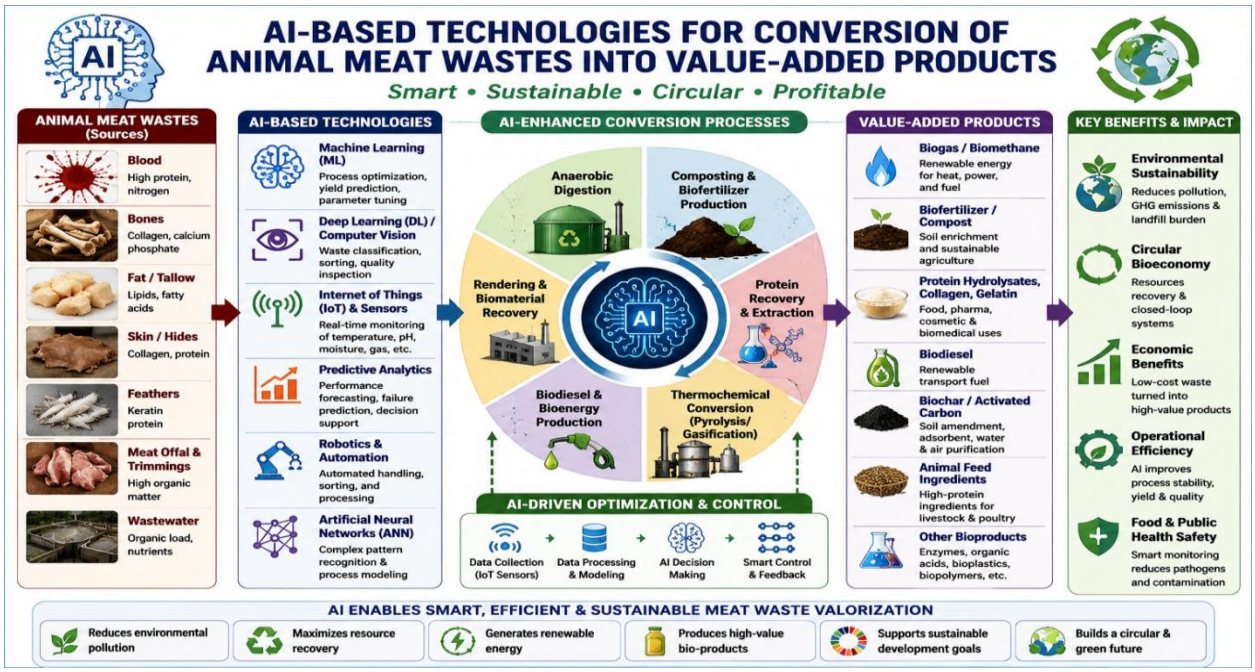


Figure 1: AI-based technologies for conversion of animal meat wastes into value-added products.

Machine learning for process prediction and optimization

Machine learning (ML) uses statistical and computational methods to identify relationships between input variables and measured outcomes. In waste-conversion systems, models such as artificial neural networks (ANNs), random forests, and support vector machines can be trained to predict process performance from feedstock composition and operating conditions. Potential applications include estimating methane production, predicting compost maturity, forecasting product yields, and identifying influential process variables. Table 1 and 2 shows the categories and the technologies of abattoir by-products. For anaerobic digestion, relevant predictors may include substrate composition, organic loading rate, pH, temperature, and hydraulic retention time. For composting, moisture, temperature, oxygen availability, and feedstock characteristics may be used to estimate maturity or process status. Studies of organic-waste treatment and composting indicate that data-driven models can assist prediction and process interpretation (Awasthi et al., 2022 and 2023; Lazrak et al., 2025; Shi et al., 2024). However, models developed using general organic wastes should not be assumed to perform equally well for blood, fat, offal, or other slaughterhouse-specific substrates without independent validation.

Table 1: Major categories of meat-processing wastes, their characteristics, and potential products

Waste type	Main sources	Major components	Environmental problems	Potential value-added products
Blood	Slaughterhouses	Protein, nitrogen, iron	High BOD and COD	Blood meal, biogas, biofertilizer
Bones	Meat processing plants	Calcium phosphate, collagen	Solid waste accumulation	Gelatin, collagen, biochar
Fat/Tallow	Rendering industries	Lipids, fatty acids	Odor and water pollution	Biodiesel, soap, biofuel
Skin and Hides	Meat industries	Collagen, protein	Putrefaction and odor	Leather, collagen peptides
Feathers	Poultry processing	Keratin protein	Slow degradation	Feather meal, amino acids
Intestinal wastes	Slaughterhouses	Organic matter, microbes	Pathogen contamination	Biogas, compost
Wastewater	Processing plants	Organic load, nutrients	Water pollution	Water recycling, nutrient

recovery

AI-assisted waste identification and classification

The composition of incoming waste streams influences the choice of recovery technology. Deep learning and computer-vision systems can analyse images to identify and classify visible materials, potentially supporting the separation of bones, fat, skin, feathers, and other solid by-products. Convolutional neural networks are widely used for image-recognition tasks, while transfer learning can reduce the amount of task-specific training data required. Research on deep learning in agriculture and food systems provides a methodological basis for these applications (Kamilaris and Prenafeta-Boldú, 2018).

Table 2: Different AI-based technologies used in meat waste valorization

AI technology	Principle / approach	Potential application	Potential benefit
Machine learning (ML)	Data-driven predictive modelling	Methane-yield and compost-maturity prediction	Decision support and process optimization
Deep learning (DL)	Multi-layer neural-network models	Image-based identification of waste materials	Automated classification
Computer vision	Image acquisition and analysis	Sorting and visual quality assessment	Faster, more consistent inspection
Internet of Things (IoT)	Connected sensors and data transmission	Real-time process monitoring	Continuous process data
Robotics	Automated mechanical handling	Sorting and movement of suitable solid by-products	Reduced manual handling
Predictive analytics	Forecasting from historical and real-time data	Anomaly detection and maintenance planning	Earlier identification of process deviations
Artificial neural networks (ANNs)	Nonlinear input-output modelling	Biogas and compost-process prediction	Modelling complex relationships

In a processing facility, automated classification could improve consistency in sorting and reduce unnecessary manual handling. However, image-based systems may have difficulty distinguishing materials that are visually similar, contaminated, overlapping, wet, or partially obscured. Blood and wastewater streams also require sensing approaches beyond conventional visible-light imaging. Therefore, practical systems may need to combine computer vision with additional sensors and human verification. Their accuracy should be reported using representative facility-level datasets, including performance across species, processing conditions, and lighting environments.

IoT and smart-sensor technologies

IoT systems use connected sensors to collect and transmit information from waste-treatment equipment. In anaerobic digestion, composting, and other biological processes, relevant measurements may include temperature, pH, moisture, oxygen concentration, pressure, and gas composition. Continuous data collection can provide a more complete picture of process conditions than occasional manual measurements. When linked to analytical software, these data can support operational alerts, trend analysis, and process-control decisions (Wolfert et al., 2017; Verdouw et al., 2021). Combining IoT with ML may help identify abnormal operating conditions, estimate process performance, and support timely corrective action. For example, sensor records can be used to track temperature and oxygen profiles during composting or to monitor pH and gas production during anaerobic digestion. The usefulness of such systems depends on sensor calibration, maintenance, data quality, connectivity, and the ability to translate model outputs into practical operating decisions. Their effects on emissions and product quality should be measured directly rather than inferred from monitoring capability alone.

Nizami et al. (2024) emphasized that AI-enabled biorefineries can convert slaughterhouse wastes, blood, fats, bones, skin, and offal into multiple value-added products, including biogas, biodiesel, collagen, gelatin, protein hydrolysates, biochar, and organic fertilizers (Table 3 and Table 4). These systems employ machine learning, deep learning, computer vision, IoT sensors, and digital twins to improve conversion efficiency, product quality, and environmental performance. In contrast, value-added compost production from manure or dead carcasses through aerobic composting is a nutrient recovery technology primarily designed to stabilize manure and produce a phosphorus-rich organic fertilizer (Mustafa et al., 2026; Rahman et al., 2011, 2014 and 2025; Won et al., 2016; Lee et al., 2009; Liu et al., 2011). According to Cordell et al. (2011), phosphorus recovery has become increasingly important because global phosphate rock reserves are finite and strategically important for future food security. Struvite ($MgNH_4PO_4 \cdot 6H_2O$) serves as a slow-release fertilizer that reduces phosphorus losses and improves nutrient-use efficiency. Rahman et al. (2023) reported that incorporating recovered struvite into poultry manure compost significantly enhances nitrogen and phosphorus retention during composting and improves fertilizer quality.

Table 3: Potential AI applications in meat-waste conversion processes

Conversion process	Potential AI application	Example parameters / inputs	Possible outputs
Anaerobic digestion	Methane-yield prediction and process monitoring	pH, temperature, loading rate, retention time	Biogas and digestate
Composting	Process tracking and maturity prediction	Moisture, oxygen, temperature	Stabilized compost
Biodiesel production	Reaction-yield and quality modelling	Feedstock lipid profile, temperature, catalyst conditions	Biodiesel
Rendering	Process and product-quality monitoring	Time, temperature, protein and fat composition	Rendered protein and fat products
Pyrolysis	Thermal-process and product-yield modelling	Temperature, heating rate, residence time	Biochar, bio-oil, and gas
Protein extraction	Extraction-yield and quality optimization	Enzyme activity, pH, temperature, time	Protein hydrolysates, collagen, gelatin

Table 4: Examples of value-added products from animal-processing by-products

Waste material	Example conversion route	Potential value-added product	Potential application
Bones	Hydrolysis and mineral processing	Gelatin, collagen-derived materials, mineral products	Food, technical, or biomedical uses, as permitted
Fat / tallow	Transesterification	Biodiesel	Renewable fuel
Feathers	Hydrolysis	Feather meal or keratin hydrolysates	Feed or industrial applications, subject to processing standards
Biodegradable meat residues	Anaerobic digestion	Biogas and digestate	Heat, electricity, and nutrient recovery
Skin and connective tissues	Collagen extraction	Collagen and gelatin	Food, cosmetic, and biomedical applications, subject to standards
Organic sludge	Appropriate biological treatment	Stabilized biosolids or compost-like products	Soil amendment, where permitted and safe

Across these applications, sensor-based monitoring and predictive analytics can complement conventional process measurements. IoT platforms provide the data infrastructure, while ML models can interpret the data and identify patterns that may not be apparent from isolated measurements. Nevertheless, the benefits should be evaluated against a clearly defined baseline, including measurement accuracy, process stability, energy use, product yield, and operating cost.

The literature relevant to AI-enabled waste valorization spans several evidence levels. Some studies address general organic-waste management or composting, while others examine digital monitoring and prediction methods that could be adapted to meat-processing residues. These studies provide useful methodological foundations, but they should not all be interpreted as direct demonstrations in slaughterhouse facilities. Table 5 should therefore be read as a summary of selected, potentially transferable research rather than as proof that each technology has already been validated for every meat-waste stream.

Table 5: Selected research relevant to AI-enabled organic-waste valorization

Technology / research area	Relevance to waste valorization	Reference listed in manuscript
AI-assisted composting	Sensor-based prediction of compost maturity and process quality	Lazrak et al. (2025)
Machine learning for composting	Prediction of compost maturity and identification of key process variables	Shi et al. (2024)
AI and waste management	Integration of AI approaches into waste-management systems	Awasthi et al. (2022)
IoT-enabled process monitoring	Monitoring and prediction for organic-waste treatment	Li et al. (2024)
AI-assisted thermochemical optimization	Potential optimization of thermal conversion conditions	Wang et al. (2024)
AI-assisted compost maturity prediction	Prediction of compost maturity using machine-learning methods	Rahman et al. (2024)

Biological conversion: anaerobic digestion and composting

Anaerobic digestion (AD) converts biodegradable organic matter into biogas under oxygen-free conditions and produces a nutrient-containing digestate. It is a potential treatment route for suitable meat-processing residues, including selected offal and wastewater fractions. However, high protein and lipid contents, rapid acidification, ammonia accumulation, and feedstock variability can destabilize digestion if loading and operating conditions are not properly managed. Process stability is therefore central to reliable methane production (Angelidaki et al., 2018; Kougias and Angelidaki, 2018). AI-based prediction and control may support AD by relating feedstock characteristics and operating variables to methane yield or process instability. ML models can analyse historical and real-time data, while sensor systems can track variables such as pH, temperature, gas production, and pressure. Such tools may help operators detect deviations earlier and adjust feeding or operating conditions. Their performance must be assessed using data from the actual substrate mixture and digester configuration; results from other organic wastes cannot automatically be generalized to meat-processing residues.

Composting is an aerobic process that stabilizes suitable biodegradable residues and produces an organic soil amendment. It may be appropriate for selected solid residues and treatment sludges when the material can be safely handled and the process is managed to achieve adequate aeration, moisture, temperature, and pathogen reduction. AI and sensor-based systems may assist by tracking temperature, moisture, oxygen, and other indicators, and by predicting process development or maturity. Research on smart composting and maturity prediction provides examples of these approaches (Awasthi et al., 2022; Lazrak et al., 2025; Rahman et al., 2024; Shi et al., 2024).

Thermochemical conversion technologies

Thermochemical processes—including pyrolysis, gasification, hydrothermal liquefaction (HTL), and hydrothermal carbonization (HTC)—can convert selected animal-derived residues into products such as biochar, bio-oil, syngas, and hydrochar. The suitability of each process depends on feedstock moisture, ash and mineral content, lipid and protein composition, and the intended product. Pyrolysis and related technologies have been investigated for organic-waste and biomass conversion, although feedstock preparation and process conditions strongly influence product yield and properties (Mashiat et al., 2026; Bridgwater, 2012; Qian et al., 2020; Qambrani et al., 2017; Shafie et al., 2012). AI may be used to model the relationships between feedstock characteristics, temperature, heating rate, residence time, and product yield. Predictive models and sensor-based control could help operators maintain target conditions and identify process deviations. Research on AI-assisted thermochemical optimization provides a basis for further development, but its application to specific slaughterhouse residues requires feedstock-specific experiments and validation (Wang et al., 2024).

Pretreatment—including size reduction, drying, dewatering, and, where appropriate, chemical or catalytic conditioning—can influence process efficiency and product quality. The energy and environmental costs of pretreatment must be included when

evaluating the overall pathway. Future studies should compare thermochemical routes with rendering, anaerobic digestion, and material-recovery options using consistent mass and energy balances and life-cycle indicators.

Recovery of proteins and other high-value biomolecules

Meat-processing by-products such as skin, bones, connective tissues, tendons, and selected blood fractions contain proteins and structural biomolecules that may be recovered for food, feed, pharmaceutical, cosmetic, or technical applications, subject to applicable safety and regulatory requirements. Collagen and gelatin are commonly recovered from collagen-rich tissues, while protein hydrolysates can be produced from suitable protein-containing streams. The value of these products depends on raw-material quality, extraction efficiency, functional properties, and microbiological and chemical safety (Jayathilakan et al., 2012; Gómez-Guillén et al., 2011; Toldrá et al., 2019). Enzyme-assisted, ultrasound-assisted, and microwave-assisted methods have been investigated to improve extraction efficiency or reduce processing time. Enzymatic hydrolysis can produce peptides with specific functional properties, while ultrasound may improve mass transfer and microwave heating may accelerate extraction. Selection of a method should consider product purity, protein functionality, energy and reagent requirements, and scale-up feasibility (Chemat et al., 2017; Chandrapala et al., 2019).

AI may support extraction-process development by modelling the effects of temperature, time, pH, enzyme concentration, and other operating variables on yield and product quality. However, the use of ML for protein and collagen recovery from meat by-products remains an emerging area, and claims of improved recovery should be supported by comparative experimental data. Recovered collagen, gelatin, and peptides may have applications in food ingredients, biomaterials, and other industries, depending on their characteristics and regulatory status (Liu et al., 2023).

AI-enabled resource recovery and the circular bioeconomy

A circular bioeconomy seeks to retain the value of biological resources through prevention, reuse, recycling, and recovery are shown in Table 6. Meat-processing residues contain carbon, nitrogen, phosphorus, minerals, lipids, and proteins that can be directed into energy, fertilizer, feed, and biomaterial pathways. Integrated biorefinery concepts aim to recover more than one product from a feedstock while reducing the amount requiring disposal. The feasibility of such systems depends on the quantity and consistency of available materials, separation requirements, process compatibility, product safety, and markets (Kirchherr et al., 2017; Nizami et al., 2023).

Table 6: Potential contributions of AI to circular bioeconomy objectives

Circular Bio-Economy Component	AI Contribution	Sustainability Benefit
Resource recovery	Smart optimization	Reduced waste generation
Renewable energy	AI-assisted digestion	Clean energy production
Nutrient recycling	Precision composting	Sustainable agriculture
Waste minimization	Automated segregation	Reduced landfill use
Carbon management	Emission prediction	Climate change mitigation
Industrial sustainability	Smart biorefineries	Circular bioeconomy development

AI can contribute to circular resource recovery by improving sorting, matching feedstocks to suitable conversion routes, monitoring process performance, and predicting product quality. In an integrated facility, data from receiving, separation, treatment, and product testing could be combined to support resource allocation and operational planning. These functions may improve traceability and process coordination, but they do not by themselves guarantee lower emissions or better resource efficiency. Such benefits need to be demonstrated through mass-balance analysis, life-cycle assessment, and techno-economic evaluation (Klerkx and Rose, 2020; Wolfert et al., 2017; Stegmann et al., 2024).

Emerging biotechnologies and precision fermentation

Microbial and fermentation-based processes offer additional opportunities to convert suitable organic fractions into microbial biomass, enzymes, organic acids, and other biochemicals. The composition and pretreatment requirements of animal-derived substrates vary considerably, and not all slaughterhouse residues are suitable for direct fermentation. Substrate selection, contaminant control, and product-specific safety requirements are therefore essential. Advances in metabolic engineering and industrial biotechnology provide a foundation for developing such processes (Nielsen and Keasling, 2016; Choi et al., 2020).

Precision fermentation uses selected or engineered microorganisms under controlled conditions to produce defined target compounds. Organic residues may potentially serve as nutrient sources or feedstock components, provided that they can be converted into a consistent and safe fermentation medium. Microbial biomass and single-cell protein have been investigated as potential products from suitable waste-derived substrates (Ritala et al., 2017; Matassa et al., 2022). AI may assist fermentation by predicting microbial growth and product formation, optimizing feeding strategies, and monitoring variables such as pH, temperature, dissolved oxygen, and substrate concentration. These applications are promising but should be distinguished from established commercial use of fermentation products made specifically from slaughterhouse wastes. Pilot studies are needed to demonstrate substrate suitability, product safety, process reproducibility, and economic feasibility (Carbonell et al., 2023).

Challenges and limitations

Despite its potential, AI-enabled meat-waste valorization faces technical, economic, environmental, and institutional barriers. A major limitation is the scarcity of standardized, high-quality datasets that represent the variability of slaughterhouse feedstocks and operating conditions that are also shown in Table 7. Models trained on small or narrowly defined datasets may not generalize across species, facilities, seasons, or treatment scales. Sensor drift, fouling, calibration errors, connectivity problems, and inconsistent data formats can further reduce model reliability. Independent validation and transparent reporting of model performance are therefore essential. Environmental performance also requires careful assessment. Poorly managed residues can generate odors, wastewater pollution, pathogens, and greenhouse-gas emissions; however, treatment processes may also

consume energy, water, and chemicals or generate secondary residues. The net benefit depends on the full treatment chain and the fate of recovered products. Economic barriers include the capital cost of sensors and automation, software and maintenance expenses, and the need for trained personnel. These costs may be difficult to justify for small facilities unless systems are modular, robust, and supported by shared services or suitable incentives.

Table 7: Key challenges and possible research responses in AI-enabled meat-waste valorization

Challenges	Impacts	Future Perspectives
High installation cost	Limited adoption	Low-cost smart technologies
Lack of technical expertise	Poor implementation	Training and capacity building
Insufficient datasets	Reduced AI accuracy	Big data integration
Sensor calibration issues	Monitoring errors	Advanced sensor development
Infrastructure limitations	Industrial constraints	Smart biorefinery systems
Regulatory barriers	Delayed commercialization	Policy and government support

Regulatory and institutional requirements are equally important. Waste segregation, transport, treatment, and end-product use must comply with relevant environmental, animal by-product, feed, fertilizer, and food-safety regulations. Unclear standards or weak enforcement can limit market acceptance, while poor segregation at source can compromise the quality and safety of recovered products. Collaboration among researchers, processors, regulators, and technology providers is needed to develop practical standards, training, and implementation pathways.

Future research directions

Future research should prioritize pilot- and industrial-scale demonstrations using well-characterized slaughterhouse feedstocks. Studies should report feedstock composition, pretreatment, operating conditions, model architecture, training and validation datasets, prediction errors, and performance under changing operating conditions. Open and harmonized datasets would facilitate reproducibility and comparison among AI models. Research should also investigate hybrid systems that combine low-cost sensors, interpretable ML models, and operator oversight rather than relying solely on complex autonomous platforms. Environmental and economic evaluation should be integrated into technology development. Life-cycle assessment and techno-economic analysis can identify whether AI-enabled monitoring and control deliver measurable improvements in energy use, emissions, water consumption, product yield, and operating costs compared with conventional practice. Further work is also needed on digital traceability, cybersecurity, data ownership, and the governance of AI-supported decisions.

Conclusion

Animal meat-processing wastes are heterogeneous materials that can serve as feedstocks for energy recovery, fertilizer production, animal-feed ingredients, biomaterials, and other value-added products. Established conversion routes include rendering, anaerobic digestion, composting, thermochemical processing, and the recovery of proteins and collagen. AI technologies—including machine learning, deep learning, computer vision, IoT, and predictive analytics—may strengthen these pathways through improved classification, monitoring, prediction, and process control. However, direct evidence from meat-processing waste facilities remains limited, and many proposed applications are extrapolated from general organic-waste treatment or other agri-food settings. The next stage of development should therefore focus on feedstock-specific validation, robust datasets, pilot-scale demonstrations, product-safety assessment, and life-cycle and economic evaluation. When implemented alongside appropriate waste segregation and regulatory oversight, AI-enabled systems could support more efficient resource recovery and contribute to a circular bioeconomy.

Acknowledgements

This work was supported by the Higher Education Acceleration and Transformation (HEAT) Project, funded by the World Bank (PIN:13303).

Competing interests

The authors declare that they have no competing interests.

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