CHAPTER
14

ARTIFICIAL INTELLIGENCE IN LIVESTOCK AND AQUACULTURE PRODUCTION SYSTEMS: INNOVATIONS, CHALLENGES, AND FUTURE DIRECTIONS

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Abstract
Artificial Intelligence (AI) is deeply reshaping animal sciences, introducing advanced tools that drive productivity, welfare, and sustainability across livestock and aquaculture systems. Wearable sensors and AI-enabled monitoring platforms deliver continuous insights into animal health, feeding behavior, and reproductive cycles, facilitating timely interventions that enhance efficiency and security. Machine learning models reinforce biosecurity by predicting zoonotic disease outbreaks, thereby protecting both animal populations and public health. In aquaculture, AI applications optimize feeding regimes, monitor water quality, and detect stress or disease in fish populations, reducing mortality and improving profitability. Despite significant challenges persisting, including limited data availability, high implementation costs, ethical considerations, and infrastructural constraints, which hinder widespread adoption. Overcoming these barriers will be essential to fully realize AI's transformative potential in advancing animal sciences and establishing resilient, sustainable systems for the future.
Keywords: *Artificial Intelligence (AI); Livestock Monitoring; Aquaculture Management; Challenges; Future Directions*

Introduction

Artificial Intelligence (AI) has emerged as a transformative technology across multiple sectors, and animal agriculture is no exception. In both livestock and aquaculture, AI-driven innovations are reshaping traditional practices by enabling precision farming, intelligent monitoring, and data-driven decision-making. These advancements are particularly significant as global demand for animal protein continues to rise, while sustainability, animal welfare, and climate resilience remain pressing challenges (Biswas et al., 2023; Guo et al., 2025).

In livestock systems, AI applications such as sensor-based health monitoring, automated feeding, and genomic prediction are improving productivity and reducing disease risks. Similarly, aquaculture has embraced AI for water quality management, biomass estimation, and stress detection, ensuring more efficient and sustainable fish production. The integration of AI with Internet of Things (IoT), robotics, and cloud-edge computing further enhances real-time decision-making, offering farmers actionable insights previously inaccessible (Nawaz et al., 2025).

Despite these innovations, several challenges deter widespread adoption. Issues related to infrastructure, sensor reliability, and the digital skills gap among farmers pose barriers to scaling AI solutions. Ethical considerations, including responsible data use and animal welfare, also demand careful attention. Addressing these challenges requires collaborative efforts among researchers, policymakers, and industry stakeholders to ensure that AI technologies are inclusive, transparent, and farmer-friendly (Biswas et al., 2023; Guo et al., 2025).

Looking forward, the future of AI in livestock and aquaculture lies in integrated approaches that combine technological innovation with sustainability and ethics. By aligning AI applications with global priorities such as the Sustainable Development Goals (SDGs), these sectors can transition toward resilient, efficient, and environmentally responsible production models. This review explores the innovations, challenges, and future directions of AI in livestock and aquaculture, highlighting its potential to revolutionize animal agriculture while ensuring long-term sustainability (Sankar et al., 2024; Rather, 2025).

AI in Livestock Monitoring and Poultry Production

1. Livestock Monitoring

AI-enabled precision livestock farming (PLF) leverages wearable and non-invasive sensor technologies, such as accelerometers, RFID tags, rumen boluses, microphones, and thermal/infrared cameras, to continuously track animal health, feeding behavior, locomotion, and reproductive status (Rosati, 2025). Streaming data are processed by machine learning and deep learning models to detect anomalies (e.g., lameness, heat stress, subclinical mastitis, respiratory distress), generate early alerts, and optimize individualized nutrition and welfare interventions, thereby improving productivity and reducing veterinary costs (Neethirajan, 2020; Zhang et al., 2021; Neethirajan, 2024; Depuru et al., 2024).

In dairy farming, AI-driven computer vision systems now enable automated cattle identification, gait analysis, body condition scoring, and real-time udder health monitoring, supporting early detection of mastitis and ketosis (García et al., 2020; Yamsani et al., 2024). Smart milking robots integrated with AI algorithms optimize milking schedules, monitor milk yield and composition, and enhance reproductive efficiency through estrus detection (Alonso et al., 2023; Alwadi et al., 2024).

2. Poultry production

In poultry production, AI applications include acoustic monitoring systems that analyze vocalizations to detect respiratory diseases, stress, or overcrowding (Ojo et al., 2022; de Carvalho Soster et al., 2025; Goyal et al., 2024). Computer vision models track flock distribution, feather condition, and pecking behavior, enabling early detection of welfare issues such as cannibalism or heat stress (Ajibola et al., 2024). Predictive analytics also optimize feed conversion ratios and growth performance, reducing mortality and improving sustainability (Neethirajan, 2020; Manikandan and Neethirajan, 2025).

AI-enabled monitoring frameworks integrate thermal imaging, weight estimation via 3D cameras, and automated behavior recognition to detect tail biting, aggression, or reduced feed intake, key indicators of stress and disease in piggery systems (Deepak et al., 2024; Choi et al., 2024). Machine learning models predict farrowing times, monitor sow health, and optimize piglet survival rates (Ho et al., 2021; Farahnakian et al., 2024). These tools are increasingly deployed in commercial pig farms, where predictive analytics improve biosecurity, reduce antibiotic use, and enhance overall herd management (Oczak et al., 2023).

Recent advances in computer vision and deep learning have enabled scalable, non-invasive monitoring across species, while edge computing and IoT integration allow real-time decision-making even in resource-limited farm environments (Chai et al., 2021). Together, these innovations mark a paradigm shift from reactive to proactive and predictive livestock management, empowering farmers with actionable insights that enhance animal welfare, productivity, and environmental sustainability (Menezes et al., 2025; Wang et al., 2025).

3. Disease Prediction

Supervised and probabilistic models (e.g., random forests, gradient boosting, and Bayesian networks) integrate clinical records, environmental variables, mobility data, and pathogen surveillance to forecast infectious disease risk, including zoonoses (Takahashi and Takahashi, 2023). Spatiotemporal modeling supports biosecurity planning, targeted vaccination, and resource allocation, while reducing false alarms via ensemble approaches and cross-validation (Mishra et al., 2020; Dubé et al., 2009). Recent advances employ recurrent neural networks (RNNs) and graph-based models to capture temporal and spatial dependencies in disease spread, improving predictive accuracy for livestock epidemics (Lin et al., 2024; Mehta et al., 2025). AI-driven early warning systems are increasingly integrated with national surveillance platforms, enhancing preparedness for zoonotic outbreaks and safeguarding economic stability and public health security (Mishra et al., 2020; Goel & Pandey, 2024).

3. AI in Aquaculture

In aquaculture, AI vision and sensor fusion systems regulate feeding (by estimating biomass and appetite from video), monitor dissolved oxygen, pH, temperature, and ammonia, and detect stress or disease signatures in real time (Jha & Bose, 2016; Rondeau et al., 2015). AI-driven models then adjust feeding rates and environmental conditions to maximize growth while minimizing feed waste and mortality. Recent studies emphasize the integration of AI with IoT and generative AI models to optimize water quality management and predict disease outbreaks in recirculating aquaculture systems (Akram et al., 2025). These innovations are particularly valuable in intensive aquaculture systems, where maintaining water quality and fish health is critical for profitability and sustainability (Jha

& Bose, 2016). Moreover, Alndiwee et al. (2025) have demonstrated that AI-enabled feeding systems can reduce feed costs by up to 20% while simultaneously enhancing growth rates. Adding AI to livestock and aquaculture systems makes them more efficient, lowers risks, and helps them produce in a way that is good for the environment. However, challenges remain, including the high cost of sensor technologies, limited digital infrastructure in rural areas, and the need for standardized datasets to improve model accuracy. Addressing these barriers will be essential for scaling AI applications across diverse production systems and ensuring that smallholder farmers benefit from these technological advances. Table 14.1 and Figure 14.1 present a summary of AI applications in livestock and aquaculture.

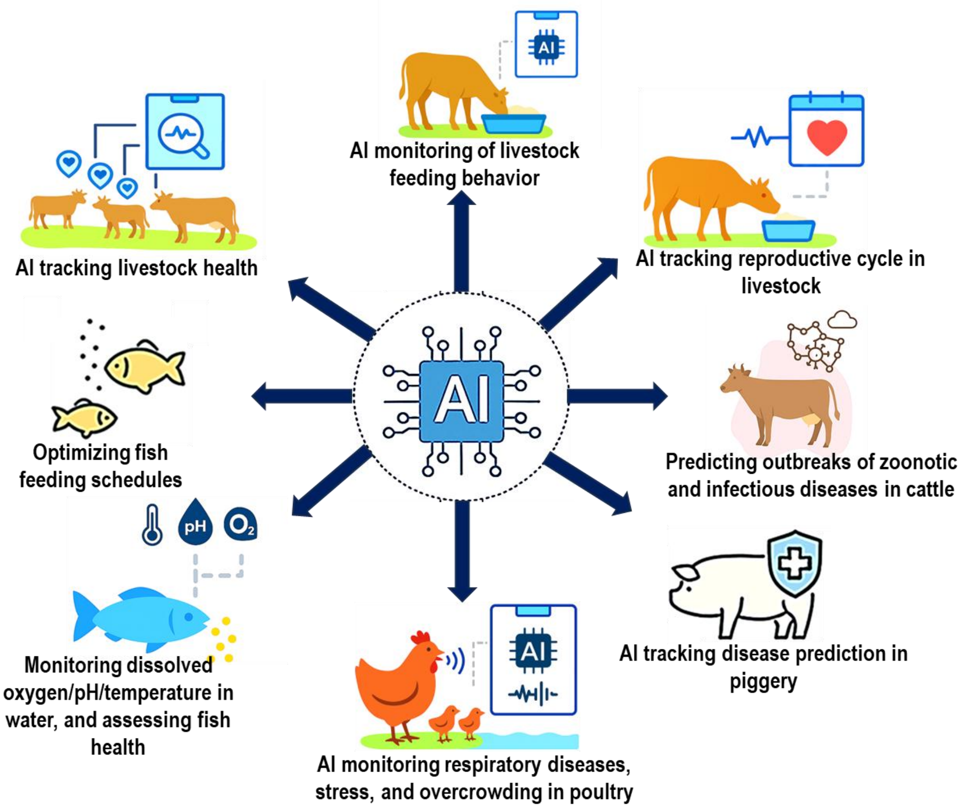

Figure 14.1. Conceptual Diagram of Applications of AI in Livestock and Aquaculture Management

Table 14.1. AI Applications in Livestock, poultry and Aquaculture production system

Sector	AI Applications	Description	Reference
Livestock	Health monitoring via wearable sensors	Smart collars, ear tags, and biosensors track physiological parameters (temperature, rumination, locomotion) for early disease detection.	Neethirajan, 2020

	Computer vision for behavior analysis	Cameras and deep learning models analyze posture, gait, and feeding behavior to detect lameness or stress.	Pantazi et al., 2016
	Reproductive cycle prediction	Machine learning models forecast estrus cycles, improving breeding efficiency and conception rates.	Wolfert et al., 2017
Poultry	Automated disease detection	AI-powered vision systems detect respiratory infections and abnormal behaviors in flocks.	Neethirajan, 2020
	Precision feeding	Algorithms optimize feed formulation and distribution based on growth stage and flock health, reducing waste and costs.	Liakos et al., 2018
	Welfare monitoring	Image recognition tracks flock density, movement, and stress indicators to improve welfare standards.	Jebari et al., 2025
Aquaculture	Feeding optimization	AI-driven platforms use underwater cameras and sensors to monitor appetite and adjust feeding schedules.	Jha & Bose, 2016
	Water quality prediction	Machine learning models analyze dissolved oxygen, pH, and ammonia levels to prevent stress and mortality.	Ragab et al., 2025
	Disease detection	Computer vision systems identify changes in fish coloration, swimming patterns, and gill movement.	Nawaz et al., 2025

Challenges in AI Adoption in Animal Sciences

Despite its promise, the adoption of Artificial Intelligence (AI) in animal sciences faces several persistent challenges that limit its widespread implementation and impact. These challenges span across technical, economic, ethical, and social dimensions, underscoring the need for interdisciplinary solutions and collaborative innovation.

1. Data Scarcity

High-quality datasets are the backbone of effective AI models, yet many regions—particularly in developing countries, lack sufficient data infrastructure. Training robust machine learning algorithms requires large, diverse, and well-annotated datasets that capture variations in animal physiology, behavior, and environmental conditions. However, data collection in livestock and aquaculture is often fragmented, inconsistent, or limited to specific commercial operations (Wu et al., 2025). Smallholder farmers, who represent the majority of producers globally, rarely have access to digital tools for systematic data collection. This scarcity leads to biased models that may perform well in controlled environments but fail under diverse real-world conditions. Furthermore, the lack of standardized protocols for data sharing and interoperability across platforms exacerbates the problem, hindering collaborative research and scaling of AI solutions.

2. Cost and Infrastructure

The financial burden of implementing AI technologies remains a significant barrier. Wearable sensors, imaging systems, and advanced monitoring platforms require substantial upfront investment, which is often beyond the reach of smallholder farmers and resource-constrained aquaculture enterprises. In addition to hardware costs, AI systems demand reliable internet connectivity, cloud computing infrastructure, and technical support, all of which are limited in rural and remote areas (Liakos et al., 2018). Maintenance and replacement costs further add to the financial strain, making long-term sustainability difficult. Without targeted subsidies, public–private partnerships, or scalable low-cost solutions, the benefits of AI risk being concentrated among large-scale commercial operations, widening the gap between industrial and smallholder farming systems.

3. Ethical Concerns

The integration of AI into animal sciences raises complex ethical issues. Data ownership and privacy are central concerns, as farmers may be reluctant to share sensitive information about herd health, productivity, or operational practices with corporations or governments. Questions about who controls and benefits from agricultural data remain unresolved, creating mistrust among stakeholders (Tripoli & Schmidhuber, 2018). Additionally, the automation of monitoring and decision-making processes may lead to labor displacement, particularly in communities where animal husbandry provides livelihoods. Ethical debates also extend to animal welfare: while AI can enhance welfare through early disease detection and stress monitoring, there is concern that intensive monitoring could reduce animals to data points, potentially overlooking broader ecological and ethical considerations. Addressing these concerns requires transparent governance frameworks, equitable data-sharing policies, and inclusive stakeholder engagement.

4. Adoption Barriers

Even when AI technologies are available, adoption is hindered by limited digital literacy and resistance to change among traditional farming communities. Many farmers lack the technical skills to operate complex AI systems or interpret data outputs effectively (Wolfert et al., 2017). Cultural factors also play a role, as some communities may be skeptical of replacing traditional knowledge with algorithmic decision-making. Resistance is further amplified by uncertainty regarding the reliability of AI predictions, especially when models are trained on datasets that do not reflect local conditions. Training programs, extension services, and participatory approaches are therefore essential to build trust and capacity among farmers. Without such support, AI risks being perceived as an external imposition rather than a tool for empowerment.

5. Regulatory and Policy Gaps

Beyond the four core challenges, regulatory frameworks for AI in animal sciences remain underdeveloped. There is limited guidance on standards for data collection, algorithm transparency, and accountability in decision-making. The absence of clear policies creates uncertainty for both developers and users, slowing innovation and adoption. Governments and international organizations must establish policies that balance innovation with ethical safeguards, ensuring that AI contributes to sustainable and equitable agricultural development (Nawaz et al., 2025). Diagrammatic representation of challenges and limitations of AI in livestock and aquaculture were presented in Figure 14.2. Also, the summary of challenges and Potential Solutions in AI Adoption for livestock and aquaculture were presented in Table 14.2.

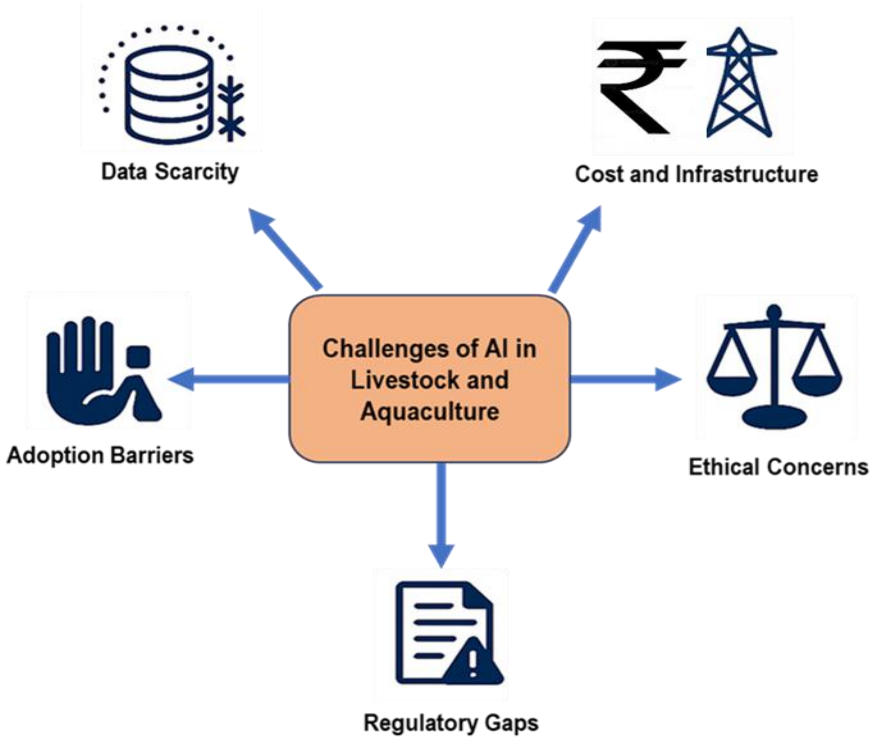

Figure 14.2. Diagrammatic Representation of Challenges and Limitations of AI in Livestock and Aquaculture.

Table 14.2. Summary of challenges and Potential Solutions in AI Adoption for livestock and aquaculture

Challenge	Description	Potential Solutions	Reference
Data Scarcity	Lack of large, diverse, and standardized datasets limits model accuracy and generalizability.	Develop open-access data repositories; promote standardized data collection protocols; encourage collaborative data sharing.	Wu et al., 2025
Cost and Infrastructure	High implementation costs and limited access to digital infrastructure hinder adoption, especially for smallholder farmers.	Subsidies and financial incentives; scalable low-cost AI tools; investment in rural connectivity and cloud infrastructure.	Liakos et al., 2018
Ethical Concerns	Issues of data ownership, privacy, and potential labor displacement create mistrust among stakeholders.	Establish transparent governance frameworks; equitable data-sharing policies; inclusive stakeholder engagement.	Tripoli & Schmidhuber, 2018
Adoption Barriers	Limited digital literacy and resistance to change among traditional farming communities.	Capacity-building programs; farmer training workshops; participatory approaches to build trust in AI systems.	Wolfert et al., 2017
Regulatory Gaps	Absence of clear policies and standards for AI use in animal sciences creates uncertainty.	Develop international and national regulatory frameworks; ensure algorithm transparency and accountability.	Nawaz et al., 2025

Future Directions for AI in Livestock and Aquaculture

Cloud-Edge Collaborative Systems

The convergence of cloud and edge computing is expected to redefine AI deployment in animal agriculture. Cloud-edge collaborative systems allow real-time data processing at the farm level while leveraging cloud platforms for advanced analytics. This hybrid architecture is particularly beneficial in rural farming environments where connectivity is limited, ensuring both responsiveness and scalability. Such systems are already being piloted in aquaculture for water quality monitoring and adaptive feeding (Fernandes, & Dmello, 2025; Guo et al., 2025).

Robotics and Automation

Robotics and automation are transforming routine farm operations. Autonomous robots are being deployed for feeding, cleaning, and health monitoring, while drones assist in environmental surveillance and stock assessment. These technologies reduce labor dependency and improve consistency in animal care. AI-driven robotics also enable adaptive responses to dynamic farm conditions, enhancing efficiency in poultry and aquaculture systems (Biswas et al., 2023).

Intelligent Monitoring and Predictive Analytics

AI-powered monitoring systems are indispensable for early disease detection, behavioral analysis, and welfare assessment. Sensor networks and computer vision can identify anomalies in feeding patterns, movement, and physiological parameters. Predictive analytics further enhance decision-making by forecasting disease outbreaks and optimizing breeding cycles. In aquaculture, AI models are being used to predict biomass and detect stress in fish populations (Guo et al., 2025).

Sustainable Resource Management

Sustainability is central to the future of animal agriculture, and AI plays a pivotal role in resource optimization. Precision feeding systems tailor diets to individual animal needs, reducing waste and improving growth efficiency. AI-driven water management and waste recycling systems contribute to environmental conservation. These innovations align with climate-smart agriculture practices and global sustainability goals (Biswas et al., 2023; Fernandes, & Dmello, 2025).

Integration with Genomics and Breeding

AI is increasingly applied to genomic datasets to accelerate selective breeding programs. Machine learning algorithms identify genetic markers associated with traits such as disease resistance, feed conversion efficiency, and adaptability to stressors. This integration enhances genetic gain and supports the development of robust livestock and aquaculture breeds. In poultry, AI-assisted genomic selection is improving productivity and resilience (Guo et al., 2025; Biswas et al., 2023).

Customized Decision Support Systems

AI-powered decision support platforms integrate data from weather, markets, and animal behavior to provide tailored recommendations. These systems democratize access to expert-level insights, empowering farmers to make informed decisions that enhance productivity and profitability. For smallholder farmers, such systems bridge the gap in veterinary and technical expertise (Biswas et al., 2023).

Policy, Ethics, and Skill Development

The success of AI adoption depends on supportive policies, ethical frameworks, and skill development.

Governments must establish guidelines for data privacy, animal welfare, and responsible AI use. Training programs are essential to equip farmers and technicians with the skills needed to operate AI systems effectively. Bridging the digital divide and fostering trust in AI technologies are critical for inclusive innovation (Guo et al., 2025; Fernandes & Dmello, 2025). Furthermore, the comparison of future directions of AI in livestock, poultry, and aquaculture were presented in Table 14.3.

Table 14.3. Comparison of future directions of AI in livestock, poultry, and aquaculture

Domain	Current AI Applications	Emerging Future Directions	Key Benefits	Challenges	Reference
Livestock	Health monitoring via sensors, automated feeding, genomic selection	Cloud-edge systems for real-time disease prediction; robotics for autonomous milking and cleaning	Improved productivity, reduced disease outbreaks, enhanced breeding efficiency	Connectivity gaps, farmer skill development, ethical concerns	Guo et al., 2025; Biswas et al., 2023
Poultry	Computer vision for behavior monitoring, automated feeding systems	AI-driven welfare assessment, predictive analytics for disease outbreaks, robotics for hatchery automation	Higher survival rates, welfare compliance, reduced labor costs	Data privacy, integration with smallholder systems	Biswas et al., 2023
Aquaculture	Water quality monitoring, biomass estimation, automated feeding	AI + IoT for climate-smart aquaculture, predictive analytics for stress/disease, drone-based stock assessment	Sustainable resource use, reduced mortality, optimized yields	Sensor reliability, high initial investment, regulatory frameworks	Fernandes, & Dmello, (2025)

Conclusion

Artificial Intelligence (AI) is rapidly emerging as a transformative force in livestock, poultry, and aquaculture systems. Its innovations, ranging from intelligent monitoring and predictive analytics to robotics, cloud-edge architectures, and genomic integration, are reshaping the way animal agriculture is practiced. These technologies promise enhanced productivity, improved animal welfare, and sustainable resource management, aligning with global priorities such as climate-smart agriculture and the Sustainable Development Goals. Despite these advances, significant challenges remain. Issues of data privacy, infrastructure limitations, sensor reliability, and the digital skills gap among farmers must be addressed to ensure equitable adoption. Ethical considerations surrounding animal welfare and responsible AI deployment further underscore the need for robust policy frameworks. Bridging these gaps requires collaborative efforts among researchers, policymakers, and industry stakeholders to create inclusive, transparent, and farmer-friendly AI ecosystems. Looking ahead, the future of AI in animal agriculture lies in integrated, cross-sectoral approaches that combine technological innovation with sustainability and ethics. By leveraging AI-driven decision support systems, genomics, and IoT-enabled monitoring, the livestock, poultry, and aquaculture sectors can move toward resilient, efficient, and environmentally responsible production models. Ultimately, the successful deployment of AI will depend not only on technological breakthroughs but also on the capacity to translate these innovations into practical, accessible solutions for diverse farming communities worldwide.

Disclosure Statement

The authors reported no potential conflict of interest.

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