

Artificial Intelligence in Livestock Robotics: A Review of Research Advances and Application Prospects

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Abstract: Livestock farming is a cornerstone of the global agricultural economy. Yet as farms expand, experience-based management falls short. It lacks efficiency and precision, along with animal welfare. Precision Livestock Farming (PLF) addresses these limits. It uses continuous, automated, individual-level monitoring and management. Livestock robots serve as key execution platforms. These platforms are increasingly enhanced by artificial intelligence (AI). We examine computer vision and deep learning for animal detection. We also cover behaviour recognition and health assessment. We review the shift from fixed-path navigation. We look at reinforcement-learning-based dynamic planning. We also cover multi-modal perception fusion. Our work highlights three research frontiers. These include large language models (LLMs) and embodied intelligence. They also include model lightweighting and edge deployment. Multi-agent coordination with UAV herding is the third. Our work also assesses general-purpose robots. It covers round-the-clock health inspection. Natural-language interaction is included too. We outline the lab-to-farm deployment gap. We cover human-animal-robot interaction. Data standardisation is addressed. Economic viability is also discussed.

Keywords: Computer Vision; Embodied Intelligence; Livestock Robots; Large Language Models; Multi-modal Perception.

1. Introduction

Livestock production remains a pillar of the global agricultural economy. Farms are expanding. Manual, experience-based management cannot keep up. It fails to meet rising demands for efficiency and accuracy, along with animal welfare.

Precision Livestock Farming (PLF) modernises animal agriculture. It uses information technologies for continuous monitoring. This monitoring is automated. It works at the individual level. It covers animal management [1].

Livestock robots are the physical enablers of PLF. They have evolved from fixed automatic feeding stations. Now they include mobile inspection systems. They also cover milking and manure-cleaning, along with herding systems.

Variable lighting is a challenge. Animal movement is unpredictable. Excreta and bedding cause occlusion. Ammonia is corrosive. These factors make farms more demanding than industrial settings. Perception is harder. Decision-making is harder. Adaptation is harder too.

AI is central to overcoming these challenges. This includes deep-learning-based vision. It also includes embodied intelligence.

We review state-of-the-art AI techniques in livestock robotics. We analyse current research hotspots. We evaluate practical deployment prospects. Our work aims to guide future research.

2. Review of Previous Work

2.1. Computer Vision and Deep Learning: From Detection to Behaviour Understanding

Computer vision provides livestock robots with environmental perception. It also gives them animal perception. Early work used background subtraction. It used

threshold segmentation. Hand-crafted features were also employed. These methods handled detection. They also handled simple behaviour classification. Over the past decade, deep learning has transformed the field.

YOLO is widely used. So are Faster R-CNN and SSD. They identify and localise livestock. Ariza-Sentís et al. (2024) reviewed more than 150 precision-farming detection studies. They found practically useful accuracy for cattle, pigs, and sheep, along with poultry. Still, they identified scarce open annotated datasets. These are the main barrier to cross-farm generalisation [2].

Behaviour recognition has progressed. It moved from binary categories. An example is standing versus lying. Now it includes fine-grained analysis. Wei et al. (2025) used a Unitree Go2 quadruped. They developed the lightweight MASM-YOLO model. It recognises six cattle behaviours. These include standing, lying, grazing, and drinking, as well as ruminating and sucking. It runs on an NVIDIA Jetson Orin NX. It achieves 90.4% mAP@0.5. It also reaches 36 FPS after TensorRT acceleration [3].

A track-based pig-inspection robot achieved strong results. It comes from the Chongqing Academy of Animal Sciences and China Agricultural University. It reached 97.7% feeding-behaviour recognition accuracy. It also achieved 99.5% MOTA in target tracking [4].

Bello et al. (2025) reviewed convolutional neural networks. They covered body-condition scoring. They also covered lameness detection. Weight estimation was included. Early disease warning was also addressed [5].

University of Georgia researchers made a prediction. They predicted broiler week-7 gait scores. They used week-2 images. This enables earlier intervention [6].

A Georgia Tech robot collects floor eggs autonomously. It works in broiler breeder houses. It is nearing commercial readiness [7].

2.2. Autonomous Navigation: From Fixed Routes to Dynamic Environment Adaptation

Livestock environments are more complex than factory AGV settings. Floors are uneven. Layouts change. Animals are moving obstacles. Early robots followed programmed paths. The Lely Discovery manure cleaner is one example. Some used magnetic guidance. More recently, SLAM has improved autonomous mobility. SLAM stands for Simultaneous Localisation and Mapping. Multi-sensor fusion has also helped. These advances work in unstructured farms.

Reinforcement learning (RL) enables navigation in dynamic environments. Sun et al. (2024) modelled cow locations as heat maps. They also modelled defecation as heat maps. They developed grid-based RL path planning. This was for manure-cleaning robots. Compared with static-obstacle methods, it retained 85.4% cleaning performance. It reduced robot-cow encounters by 67.6%. It explicitly incorporated animal behaviour into planning [8].

Wang et al. (2024) validated a herding strategy. It uses reinforcement learning. They used UAV-UGV cooperative experiments. UAVs guided autonomous ground vehicles. They moved toward target locations. The experiment did not involve real livestock. Even so, it provides methodological references. These references help future intelligent herd management systems [9].

Wang et al. (2025) reviewed navigation sensor fusion. They combined LiDAR and depth cameras, along with thermal infrared. This was in livestock robots [1].

2.3. Multi-modal Perception Fusion

Single sensors are insufficient in livestock settings. RGB

cameras are light-sensitive. Thermal infrared cannot identify individuals. LiDAR does not capture physiological states. Multi-modal fusion is therefore essential.

Li et al. (2025) combined several technologies. They used binocular stereo vision. They added GPS and IMU. They employed YOLOv8s object extraction. Extended Kalman filtering was also used. This formed a contactless virtual electric fence. It determined whether cattle were within the fence. It achieved 97.8% accuracy. This is 4.3% above conventional algorithms. It also avoided smart-collar stress [10].

A sheep-farm epidemic-prevention robot used DAENet. DAENet stands for dual-attention ENet semantic segmentation. It achieved 0.9453 mIoU. It also achieved over 90% spray coverage [11].

These results show one thing. Multi-modal fusion improves robustness. It also improves functionality.

3. Current Research Hotspots

3.1. Large Language Models and Embodied Intelligence for Livestock Farming

During 2025-2026, LLMs entered livestock applications rapidly. These include ChatGPT and DeepSeek, along with Qwen. 2026 is widely described as the first year of AI agents. Several organisations project China's smart-agriculture market will exceed RMB 134 billion [12].

Livestock LLMs have progressed. They moved from question-answering tools. Now they are AI agents. These agents can perceive. They can reason. They can also act. Notable examples include:

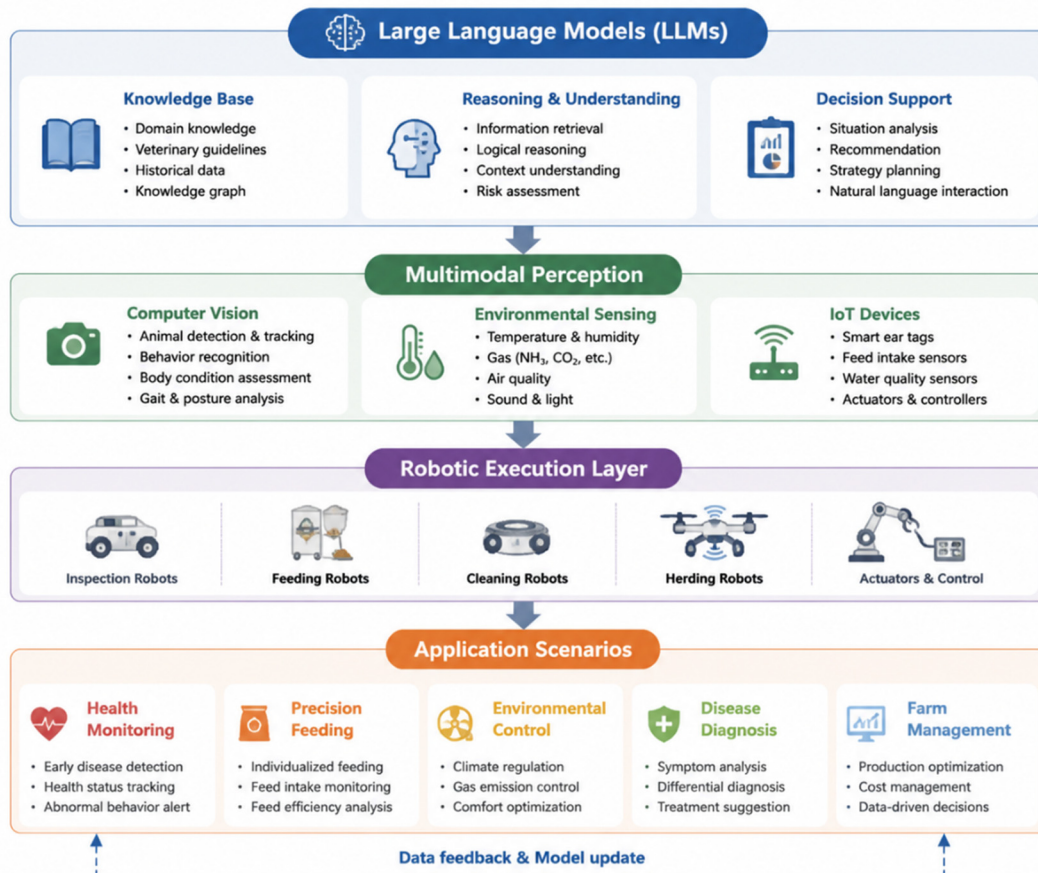


Figure 1. shows the Framework. It covers LLM-enabled Intelligent Livestock Management

1. Muyuan-Alibaba Cloud Pig-Farming LLM (2026): Muyuan and Alibaba Cloud built a pig-farming agent. It is Qwen-based. It is a full-chain agent. It uses 2 billion daily data points. These come from 3.3 million smart devices. Inspection robots detect anomalies. Environmental sensors do too. Smart ear tags are also used. They detect temperature anomalies. They also detect feeding anomalies. They issue treatment recommendations within seconds. Health-monitoring time drops from 20 minutes to near-instant. Efficiency improves more than 100-fold [13].

2. SheepDoctor (2025): This is a diagnostic model. It uses LLaMA2-13B-Chinese. It uses LoRA fine-tuning. It also uses a knowledge graph. This graph covers 207 sheep diseases. It outperforms general-purpose models. These include GPT-4o and Kimi [14].

3. Hd-LLM Environmental Management Framework (2025-2026): This framework was published in Expert Systems with Applications. It is GPT-2-based. It adds physics-guided forecasting. It also adds neuro-symbolic reasoning. It was tested in northern Chinese meat-sheep barns. It reduced ammonia-prediction MAE by 56.4%. It also produced interpretable risk reports [15].

4. Taiwan Livestock AI Assistant (2026): ATARI Taiwan and the National High-Performance Computing Centre created 'Pig Q&A AI'. It combines generative AI with computer vision. It provides advice through a LINE chatbot. It uses Taiwanese-dialect voice interaction. It improved weaning rates by 3-5%. It also improved growth rates by 3-5%. It saved about one labour hour per worker daily [16].

Livestock LLM applications now form a closed loop. Perception comes through sensors and cameras. LLM-driven

cognition follows. Decisions are made. Execution is done by robots or actuators [12].

Retrieval-Augmented Generation (RAG) reduces hallucinations. Domain knowledge graphs also help. This is in veterinary contexts [17].

3.2. Model Lightweighting and Edge Deployment

On-board computing is limited. Battery capacity is limited too. Farm networks are weak. These factors constrain cloud-dependent livestock robots. Lightweight models are essential. Edge deployment is also essential.

MASM-YOLO replaces the YOLOv11s backbone. It uses a lightweight StarNet network. It uses 4.0M parameters. It also uses 18.2G FLOPs. This cuts parameters by 57.4%. It still delivers 36 FPS on Jetson Orin NX [3].

AgriYOLOP (2025) is not specifically designed for livestock robots. Even so, its multi-task perception architecture provides valuable reference. This reference helps agricultural robot navigation. It uses an NVIDIA RTX 4060 platform. Its inference speed cannot be directly compared with lightweight edge models. These are deployed on embedded devices. It handles obstacle recognition. It also handles traversable-area segmentation. It achieves 96.7% mAP50. It is orchard-focused. Still, its architecture informs livestock perception [18].

The Hd-LLM Frequency-Aware Adapter does something similar. It compresses GPT-2 capabilities. This is for edge-based farm environmental prediction [15].

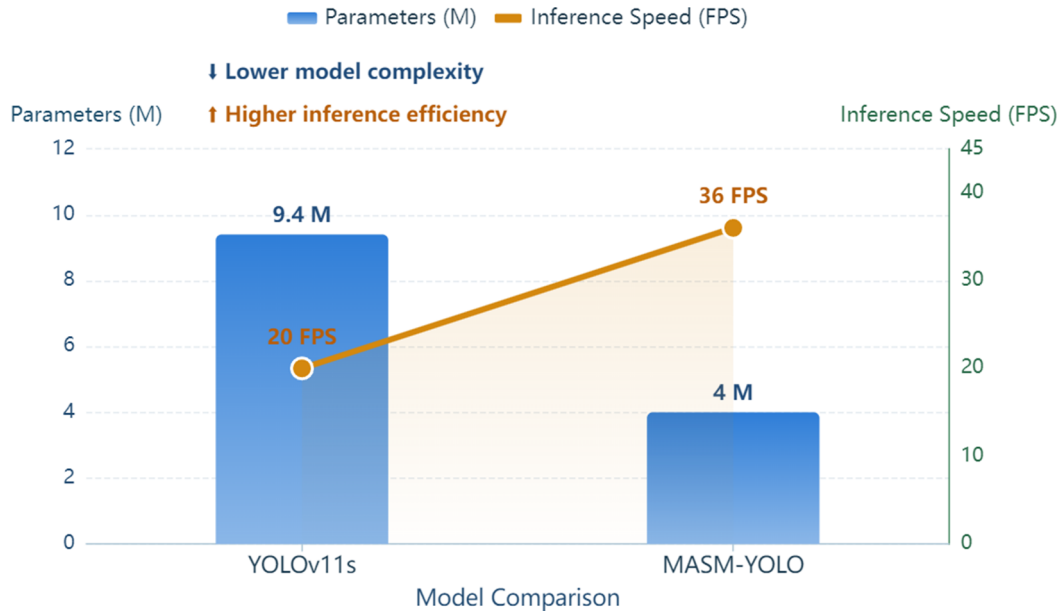


Figure 2. shows the model-lightweighting trend:

3.3. Multi-agent Coordination and UAV Herd Management

One robot may lack sufficient range. It may also lack capacity. Multi-agent coordination extends coverage. Research focuses on multi-UAV herding. It also covers dynamic scheduling. This is for multiple manure-cleaning robots [8,9]. Rural 5G coverage is expanding. This makes hybrid systems increasingly feasible. Cloud-based coordination is used. Autonomous edge execution is also used.

4. Application Prospects in Livestock Robotics

4.1. From Specialised Function Robots to General-Purpose Farming Robots

Most livestock robots specialise in specific tasks. These include milking and manure cleaning, along with inspection. Combining embodied intelligence with LLMs could enable

general-purpose machines. These would be multi-task machines. LLMs would handle semantic understanding. They would also handle high-level planning. An example is 'check the lame cow in the third pen.' Robots would execute motion. They would also execute manipulation. Similar layered architectures have been demonstrated. They were shown in factory logistics. They were also shown in home services. This supports their transfer to farming [12,17].

4.2. Round-the-Clock Health Inspection and Early Warning

Advances in computer vision will help. Multi-modal perception will help too. These advances will move livestock robots from passive inspection. Now they will provide early warning. Thermal imaging can reveal sub-health signals. So can gait analysis. Vocalisation recognition also helps. Feeding-behaviour tracking does too. These signals appear before clinical symptoms. Muyuan reduced health detection time. It dropped from 20 minutes to seconds. This expands the early-intervention window. It also lowers mortality. Treatment costs drop too [13]. Lightweight models should help. Stronger edge computing should too. These will reduce adoption barriers. This is especially true for small and medium farms.

4.3. Human-Robot Collaboration via Natural Language Interaction

LLM-driven natural-language interfaces are useful. They let farm workers control robots. No complex panels are needed. Staff can issue plain-language requests. An example is 'check the three animals with the largest drop in feed intake today.' They can receive structured reports. This approach is especially valuable. Skilled-labour shortages are severe [17,19].

4.4. Remaining Challenges

This promise is real. Still, scalable AI deployment in livestock robotics faces four main hurdles:

1. Lab-to-farm deployment gap: Toure et al. (2026) made a finding. 67% of livestock robotics and autonomy studies still depend on simulation. They do not use dynamic farm validation. Cross-farm generalisation remains a bottleneck. Sim-to-real transfer is also a major bottleneck [20].

2. Robot-animal interaction: Livestock robots must coexist with animals. The Georgia Tech egg collector had to 'negotiate' with hens. It did this to clear a path [7]. Animal acceptance remains underexplored. So does stress. Interaction safety is also underexplored.

3. Data standardisation and sharing: Farm data are fragmented. They are heterogeneous. They are non-standardised. Annotated datasets remain scarce [2]. Standards are missing. Sharing mechanisms are missing too. These gaps hinder large-scale AI training. They also hinder iteration.

4. Economic viability: Farming margins are thin. They require clear investment returns. Most solutions remain in R&D stages. Some are in pilot stages. Large-scale commercial cost-effectiveness is unproven [1].

5. Conclusion

AI is broadening livestock-robot capabilities. It is deepening them too. The field has advanced from object detection. Now it includes embodied agents. It has moved from single sensors. Now it uses multi-modal fusion. It has

moved from fixed routes. Now it uses RL-based decisions. These advances improve perceptual precision. They improve decision intelligence. They also improve operational autonomy.

LLMs create a path. Embodied intelligence does too. This path leads toward fully autonomous farming robots. Lightweight models make practical rollout more feasible. Edge deployment does too.

Over the next five to ten years, livestock robots are expected to progress. They will move from specialised task substitution. They will reach AI-assisted decisions. They will achieve multi-task coordination. Ultimately, they will reach large-scale autonomous farming. This transition requires close collaboration. Computer science must contribute. So must veterinary and animal sciences, along with agricultural engineering.

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