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AI-Empowered Livestock Monitoring in Captive or Free-Range Breeding: A Review

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ABSTRACT

Timely health monitoring is crucial for preventing livestock diseases throughout the breeding process. Conventional Livestock Health Monitoring (LHM) relies on manual efforts, achieving acceptable accuracy but suffering from low efficiency. Modern LHM integrates artificial intelligence to enhance both accuracy and efficiency in monitoring practices. This study reviews and evaluates over 200 research papers on intelligent monitoring in livestock, focusing on two breeding scenarios: Captive and Free-range. It examines various species, including pigs, cattle, sheep and horses and conducts a comparative analysis of three key tasks: livestock identification, growth estimation and behavior/posture detection. By highlighting common challenges and technical requirements across species, the study provides insights for selecting suitable monitoring technologies and designing tailored systems for each breeding scenario. The scenario-based classification enables customized LHM solutions that improve versatility and adaptability across different farming environments. The study reveals common challenges in cross-species monitoring and outlines future research directions to address technical limitations and practical implementation barriers in AI-driven livestock health management.

Key words: AI technology, Behavior, Growth estimation, Livestock breeding, Livestock health monitoring, Livestock identification, Posture detection.

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In livestock breeding, livestock health monitoring (LHM) plays a vital role in disease prevention and production efficiency. As shown in Fig 1, breeders mark livestock offspring for ongoing monitoring. They assess development by measuring growth metrics such as body size and weight and observing posture, behavior and social activities to evaluate overall health. Upon maturity, breeders may sell, slaughter, or continue breeding the livestock. Regular LHM throughout the breeding cycle helps identify potential problems promptly, improving livestock quality and yield, preventing diseases, optimizing breeding strategies and promoting the sustainable development of animal husbandry.

Conventional LHM methods depend on manual measurements and empirical judgments, resulting in high information collection costs, poor real-time performance and low accuracy. In contrast, modern LHM utilizes artificial intelligence technologies, offering automation, efficiency and precision. As research advances, numerous scholars have summarized developments in various dimensions. For instance, Bretas *et al*. (2024) review precision livestock farming technologies for monitoring grazingland, emphasizing their role in enhancing productivity and sustainability. AlZubi *et al*. (2023) highlight the transformative role of artificial intelligence in predicting and diagnosing animal diseases, focusing on its potential to improve animal health management, while Antognoli *et al*. (2025) explore how computer vision improves efficiency and animal welfare in dairy farming. These reviews provide valuable technological insights and lay a methodological foundation for the field.

However, despite the thorough exploration of technical applications in existing research, a critical issue is often overlooked: The effectiveness of these technologies is highly dependent on the specific physical scenarios and environmental constraints in which they are deployed. Most reviews juxtapose technologies validated in diverse environments-varying in background, spatial layout and data collection conditions-without a scene-aware classification framework. This approach fails to address the crucial question of “which technology is best suited for which breeding model,” which is vital for practical applications. The limitations arise from the fundamental differences between Captive breeding (*e.g.*, closed barns) and Free-range breeding (*e.g.*, open pastures), including background complexity, animal density, installable equipment and data acquisition methods. These differences directly impact the feasibility, robustness and economic viability of technological solutions.

To address the aforementioned research gap, this study systematically reviews and reassesses existing intelligent monitoring research in livestock, focusing on two primary breeding scenarios: Captive and Free-range. The research encompasses various livestock species, including pigs, cattle, sheep and horses and conducts a comprehensive comparative analysis centered on three key monitoring tasks: Livestock identification, Growth estimation and Behavior and Posture detection. By summarizing common challenges and technical requirements across different species, this study provides theoretical foundations and practical guidance for selecting monitoring technologies and constructing systems tailored to various breeding scenarios, thereby promoting the intelligent advancement of precision livestock farming. The main contributions of this paper are as follows:

(1) We have collected and analyzed 207 LHM-related papers in recent years. Through organizing and summarizing these gathered resources, we aim to provide readers with the latest trends and research findings in the field of LHM.

(2) This paper studies the LHM in captive breeding and free-range breeding respectively and comprehensively evaluates the health status of livestock from three key monitoring tasks: Livestock identification, growth estimation, Behavior and posture detection.

(3) The study systematically analyzed monitoring tasks and modeling approaches in the LHM component, revealing challenges such as data heterogeneity and insufficient model generalization ability. Based on current research trends, this paper describes existing technical limitations through three dimensions: Architecture optimization, multimodal fusion and algorithm innovation, providing new directions for the LHM field.

Research of livestock health monitoring

Scenario of breeding

Hunter (1996) introduced the concepts of captive and free range systems. To better analyze and evaluate existing studies, we integrate these concepts into AI enabled LHM farming environments and establish a classification framework along four dimensions: spatial characteristics, monitoring equipment type, environmental controllability and data collection characteristics. Details are provided in Table 1.

The study prioritized the type of equipment, followed by spatial features, environmental descriptors (keywords: “barn/fence” vs. “Pasture/grazing”) and data collection conditions. When studying elements containing both scenarios, the classification was determined by the dominant features (andgt;60%) across all four dimensions.

Research of livestock health monitoring

We discussed LHM based on two scenarios (Fig 2) and analyzed three key monitoring tasks: livestock identification, growth estimation and behavior and posture detection. First, livestock identification ensures each animal receives individualized attention and records, providing essential data for management. Second, growth estimation involves evaluating body condition, body weight and body size. Body condition detection assesses nutritional status to promote

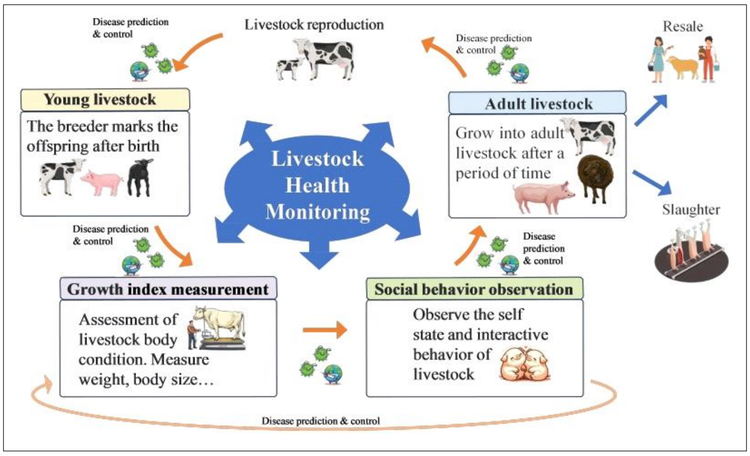

Fig 1: Livestock breeding process.

Table 1: Indicators of captive and free-range breeding in AI-enabled LHM.

Dimension	Captive breeding indicators	Free-range breeding indicators
Monitoring equipment type (MET)	Cameras (fixed/handheld), CCTV, Indoor sensors, RGB-D, Vidicon	GPS, RFID, UAVs, LiDAR, Accelerometers (ACC), Wide-area camera or vidicon
Spatial characteristics (SC)	High breeding density, limited activity space	Low breeding density, large activity space
Environmental controllability (EC)	≥ 3 parameters artificially controlled	>80% natural environment Highly variable, prone to interference
Data collection characteristics (DC)	Standardized, high-resolution	

optimal growth and production. Weight detection monitors growth rates and trends, allowing adjustments in feeding and management. Body size detection analyzes physical characteristics, helping breeders implement effective breeding programs. Finally, Behavior and posture detection provides insights into activity levels and physiological states, enabling the identification of sick or abnormal livestock.

These three parts are interconnected to form a complete livestock monitoring framework. In two different scenarios, the use of various monitoring technologies combined with data analysis and intelligent algorithms can accurately identify the health status of livestock in this scenario, timely identify potential disease risks, effectively plan feeding strategies and improve production efficiency.

Research method

We conducted a structured search across three platforms-Web of Science Core Collection, DBLP and Google Scholar-covering the period from 2017-01-01 to 2025-10-09. Queries were organized into three thematic blocks: (A) identification (identification/re-identification/face recognition/ear tag/muzzle, multi-object tracking, counting); (B) growth estimation (body weight/size, morphometry, body condition score, BCS); and (C) Behavior and posture (posture/pose, social behavior, lameness, rumination, estrus, aggression). Each block was combined with species terms (livestock; pig/swine; cattle/cow/bovine; sheep/ovine; goat/caprine; horse/equine) and method terms (deep learning, computer vision, YOLO, transformer, *etc.*) using the AND operator and further constrained by scenario terms (captive/barn/pen/indoor/slaughterhouse and free range/pasture/grazing/rangeland/paddock/outdoor). The three blocks returned 121, 97 and 88 records in Web of Science; 131, 99 and 80 in Google Scholar; and 103, 81 and 127 in DBLP, respectively.

Search results from all platforms were exported and merged, then de-duplicated by DOI and by normalized titles (case-insensitive, punctuation removed). Inclusion criteria required AI/computer-vision–based monitoring of livestock species, publication within the specified time window and accessible full text. After screening, 207 studies were retained for synthesis. Their distribution is shown in Fig 3 and the complete list of all 207 studies is provided in the appendix.

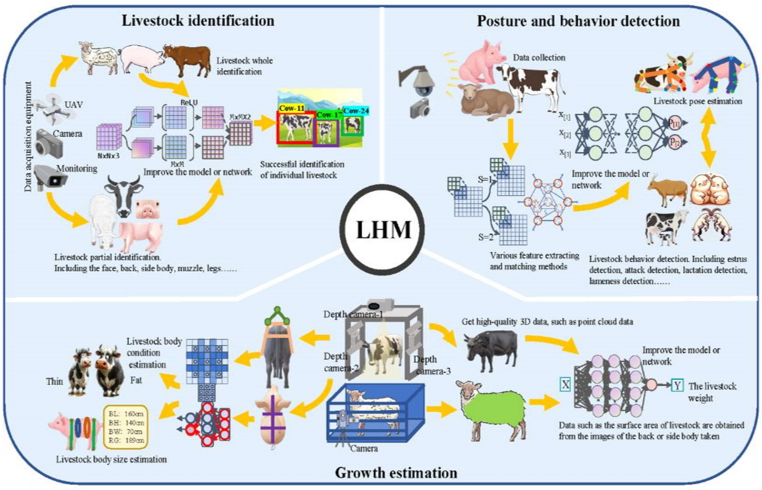

Fig 2: Research of livestock health monitoring.

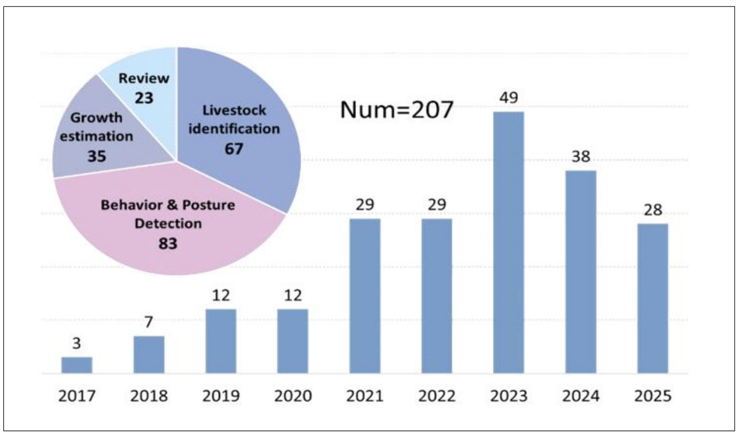

Fig 3: Distribution of literature on AI-enabled livestock health monitoring (2017-2025).

Livestock identification

In livestock breeding, the accurate identification of livestock individuals is the basis of breeding management and disease monitoring. The identification method based on AI technology has become the mainstream method, which can realize 24/7 real-time monitoring and identification of livestock and help managers find abnormal conditions in time. Accurate recognition can be achieved by extracting the body features of livestock.

Captive breeding

Captive breeding provides a structured setting where animal behavior can be closely monitored and analyzed. The implementation of fixed surveillance systems, positioned strategically around enclosures, allows for continuous observation and data collection, enabling researchers to gather insights into individual animal behaviors and interactions.

Multi-object tracking algorithms: Lu *et al*. (2024) and Yang *et al*. (2025) achieved 99.8% and 98.8% tracking accuracy in complex environments and low-light pig farms respectively through rotated bounding box detectors and spatiotemporal dynamics analysis. Myat Noe *et al*. (2023) improved black cattle tracking accuracy to 76.2% *via* algorithm comparisons.

Lightweight biometric recognition: Zheng *et al*. (2023)'s six-layer convolutional model, Ruchay *et al*. (2024) transfer learning framework and Li *et al*. (2023) MobileViTFace achieved embedded deployment for cattle face (98.37%) and sheep face (97.13%) recognition. Yang *et al*. (2023) enhanced cattle MOTA to 96.88% using deformable convolutions.

Unsupervised feature optimization: Lu *et al*. (2023) developed a key region module for unsupervised fine-grained feature extraction, achieving 98.37% cattle recognition accuracy.

Free-range breeding: In free-range breeding scenarios, the identification of livestock requires a more dynamic approach due to the inherent mobility and unpredictability of animals. Scholars emphasize the importance of blending technology with behavioral insights to effectively track animals in open environments.

IoT tracking systems: Voulodimos *et al*. (2010)'s RFID management system and Pretto *et al*. (2024) visual ear mark recognition (89% precision) formed dual-mode individual tracking. Natori *et al*. (2019) integrated GPS/accelerometers to establish grazing cattle activity models.

Drone-based monitoring: Soares (2024) applied Ford-Fulkerson algorithm to reduce counting errors to 2.34%. Liu *et al*. (2021) developed a real-time app that compressed transmission latency below 500ms with intelligent UAV path guidance.

Multimodal recognition: Sun *et al*. (2024) enhanced MixFormer trackers to handle posture variations (75.79%

Table 2: Livestock identification of livestock.

Scenarios	Reference	Species	MET	SC	EC	DC	Body part	Performance
Free-range breeding	Natori *et al*. (2019)	Cattle	ACC	Grazing	Na-env	Time series	Whole	NR
	Pretto *et al*. (2024)	Cattle	RFID	Pasture	Na-env	Event log	Face	Precision: 89%
	Xu *et al*. (2022)	Sheep	Camera	Pasture	Na-env	Images	Whole	MAE: 2.8, RMSE: 4.5
	Soares *et al*. (2021a)	Cattle	UAVs	Pasture	Na-env	Drone video capture	Whole	Multiple count result
	Cao *et al*. (2023)	Sheep	Camera	Grazing	Na-env	Drone imagery	Whole	Precision:97.1% AUC:
	Sun *et al*. (2024)	Goat	Camera	Outdoor	Na-env	Images	Whole	75.79%, Precision:74.28%
	Liu *et al*. (2021a)	Cattle	UAVs	Outdoor	Na-env	Drone video capture	Whole	Transmission delay <500 ms
Captive breeding	Yang *et al*. (2025)	Pig	Vidiction	Pens	Controlled	10fps video recording	whole	MOTA:98.8%, IDF1: 99%
	Lu *et al*. (2024)	Pig	Vidiction	Closed hut	Controlled	25fps video recording	whole	mAP: 80.05%
	Huang *et al*. (2023)	Pig	Vidiction	Slaughterhouse aisle	Controlled	25fps video recording	Back	Accuracy: 98.37%
	Ruchay *et al*. (2024)	Cattle	CCTV	Barn	Controlled	30fps video recording	Face	Accuracy: 97.1%
	Yang *et al*. (2023)	Cattle	Camera	Monitored farm	Controlled	15 cameras	Whole	MOTA: 96.88%
	Li *et al*. (2023)	Sheep	Camera	Pen	Controlled	60fps video recording	Face	Accuracy: 97.13%
	Guo *et al*. (2023a)	Sheep	Camera	Monitored farm	Controlled	high-resolution imaging	Face	Accuracy: 92.75%

Footnote: MET=Monitoring equipment type, SC=Spatial characteristics, EC=Environmental controllability, DC=Data collection, NR: Not reported in the original paper, Na-env: Natural environment. "Controlled" means artificially controllable, for example: light, temperature, humidity, *etc*.

AUC), while Hassan-Vasquez (2022) combined deep learning with GPS for activity boundary mapping.

Summary

Table 2 summarizes studies on livestock identification tasks (details in the Appendix). Significant differences exist between captive and free-range breeding in the application and development of identification technologies. In confined environments, identification accuracy is generally stable and exceeds 94%, with Odo *et al*. (2025) achieving up to 95% accuracy using high-frame-rate CCTV. However, this reliance on controlled conditions raises concerns about the generalizability of findings to real-world scenarios.

Most studies in confined spaces focus on RGB-D cameras and deep learning algorithms. For instance, Lu *et al*. (2024) reported 97.5% accuracy under stable conditions, showcasing technological advancements. Nonetheless, limitations such as lighting variations and animal behavior must be acknowledged, as these can affect performance in practical applications.

In contrast, accuracy in free-range breeding is more variable, heavily influenced by weather and environmental conditions. Zhang *et al*. (2022) found a significant decrease in drone monitoring accuracy during adverse weather, while Huang *et al*. (2023) reported 84% accuracy through multi-sensor data fusion-less than that in captive environments. Addressing the need for robust sensor fusion techniques and adaptive algorithms is essential.

In summary, although captive settings foster the development of high-accuracy identification technologies, future research must tackle the limitations in fluctuating conditions. This could involve hybrid approaches that integrate diverse data sources, enhance algorithm adaptability and improve sensor robustness for reliable performance across different livestock species and breeding contexts.

Growth estimation

The estimation of livestock growth involves detecting body condition, weight and body size, which are key parameters for evaluating their development and health (Machebe N.S., 2016). Regular monitoring of these factors enables breeders to understand livestock growth status and adjust feeding and management practices to ensure adequate nutrition and optimal growth conditions, thus enhancing breeding efficiency and production performance. Fig 4 illustrates two typical AI-based approaches for detecting growth indicators.

Captive breeding

In captive breeding, livestock growth is primarily influenced by human management rather than natural environmental factors. This controlled setting allows breeders to monitor growth closely and adjust feeding strategies based on regular measurements of body shape, weight and size to ensure healthy development.

Body condition monitoring: Basak *et al*. (2023) demonstrated 94.6% body composition prediction in pigs using ultrasound-SVR integration, while He *et al*. (2023a) developed YOLOX-based posture scoring achieving 0.85 F1-score.

Contactless weight estimation: LiDAR-PointNet++ systems attained 3.2% prediction error in cattle Hou *et al*. (2023), contrasting with RGB-D LiteHRNet's 14.6% MAPE for sheep He *et al*. (2023b).

3D morphometrics: Weng *et al*. (2023) and Ling *et al*. (2022) established Kinect V2-based pig measurement pipelines (2.1cm MAE), enhanced by Lu *et al*. (2025) 's GCN-mesh refinement (3.58% MAPE).

Free-range breeding

In free-range breeding, livestock growth is more influenced by natural factors than by human intervention. This environment necessitates a different evaluation approach, considering behavioral characteristics, social relationships and autonomous selection abilities to comprehensively assess the health status of livestock.

Vision-based systems: Bai *et al*. (2025) enabled smartphone-based cattle weight estimation (97%

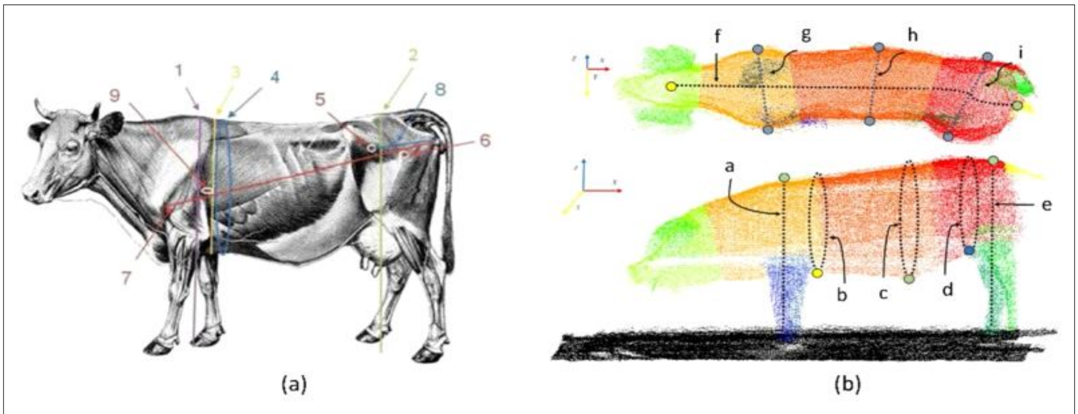

Fig 4: (a) Growth estimation based on image analysis, with measurements: 1-9 representing various body dimensions. (b) Growth estimation using 3D stereo reconstruction technique, with measurements a-i representing different body dimensions.

precision) through multi-scale fusion networks. Garcia *et al*. (2021) identified weight anomalies with a gradient boosting model (R^2 = 0.92).

Sensor Integration: Vaughan *et al*. (2017) 's tomography sensors (<1% error) and Simanungkalit *et al*. (2020) 's WOW systems demonstrated 100% repeatability in pasture conditions.

Predictive analytics: Abdelhady *et al*. (2019) achieved 98.75% accuracy in sheep weight prediction using K-means clustering. Sultana *et al*. (2022) compared three nonlinear models for predicting yearly cattle weight, showing that the Brody model offers better fit statistics for various cattle genotypes in Bangladesh.

Summary

Growth estimation in livestock differs significantly between captive and free-range breeding, each presenting unique challenges for technology application. In captive settings, researchers have achieved over 94% accuracy using advanced imaging and algorithms, thanks to stable monitoring and controlled management (Table 3). Fig 5 highlights that weight measurements account for 36% of growth estimation methodologies in both settings, with body condition assessments contributing 28% in captivity and 20% in free-range environments. The trend indicates an increasing emphasis on optimizing technology for accurate assessments, particularly in captive breeding.

However, the reliance on controlled environments raises concerns about the transferability of these findings to real-world scenarios, where factors like animal stress and varying behaviors can significantly affect growth outcomes. This emphasizes the need for caution when interpreting results from ideal conditions. Moreover, species-specific differences in growth estimation methods call for tailored approaches. For example, pigs benefit from visual and tactile data, while cattle and sheep typically rely on conventional weight and body condition metrics, indicating that a one-size-fits-all solution may not be effective.

Although advancements in sensor technology offer new opportunities for growth estimation, they also introduce complexities that can hinder practical applications. While multiple sensors enhance sensitivity to behavioral changes, they complicate data management, underscoring the preference for simpler monitoring solutions in real-world settings.

Behavior and posture detection

Monitoring livestock behavior and posture enables breeders to quickly assess health, emotional states and growth, facilitating early detection of diseases or abnormalities. Key posture indicators include standing and lying positions, head posture and leg alignment, which reveal activity levels and comfort, as well as potential musculoskeletal issues. Additionally, behavior patterns serve as vital indicators of health and welfare; timely

Table 3: Growth estimation of livestock.

Scenarios	Reference	Livestock	MET	SC	EC	DC	Task	Methods	Performance
Free-range breeding	Simanungkalit *et al*. (2020)	Cattle	Weighing platform	Grazing	Na-env	Weight numbers	Weight	WOW system	Min error: 3.2%
	Bai *et al*. (2025)	Cattle	Phone	Grazing	Na-env	Images	Weight	Deep learning	Accuracy: 97%
	Abdelhady *et al*. (2019)	Sheep	Phone	Pen	Na-env	Images	Weight, Size	K-means	Accuracy: 98.75%
	Garcia *et al*. (2021)	Cattle	NR	Grazing	Na-env	Weight numbers	Weight	Machine learning	MAE <5.4kg
Captive breeding	Basak *et al*. (2023)	Cattle	Load cells + IR sensors	Barn	Controlled	Multi-sensor data	Condition	Machine learning	Accuracy: 98.46%
	He *et al*. (2023)	Cattle	Camera	Pen	Controlled	Images	Condition	YOLOX-BCS	mAP: 80.06%
	Hou *et al*. (2023)	Cattle	LiDAR	Channel	Controlled	Point cloud	Weight	PointNet++	MAPE: 3.2%
	He *et al*. (2023)	Sheep	RGB-D	Channel	Controlled	RGB-D images	Weight	LiteHRNet	MAPE: 14.61%
	Lu *et al*. (2025)	Cattle	Camera	Channel	Controlled	Point cloud	Size	Point cloud	MAPE:3.58%
	Liu *et al*. (2023)	Pig	Camera	Pen	Controlled	Standard images	Size	YOLOv5	AP: 99.21%
	Du *et al*. (2022)	Cattle, Pig	Kinect v2	Channel	Controlled	Point cloud	Size	Pointcloud	MAPEs: 0.1
	Huang *et al*. (2019)	Cows	Camera	Pen	Controlled	25fps recording	Condition	Single Shot Multibox	N R
	Win *et al*. (2021)	Pig	Camera	Channel	Controlled	Fixed-position image capture	Size	Laser Projection	N R

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monitoring can identify abnormal behaviors and early signs of disease or environmental stress, allowing for prompt preventive measures.

Captive breeding

In captive breeding scenarios, livestock are often affected by spatial limitations and human intervention and their Behavior and posture may exhibit certain characteristics. Livestock may exhibit more regular and repetitive behavior patterns in captive environments, such as walking back and forth, standing or lying down. Monitoring the Behavior and posture of captive livestock can help evaluate their adaptation to captive conditions, explore their physiological and psychological states and identify potential health issues or behavioral abnormalities.

Zia *et al*. (2023) established the CVB dataset with 502 natural-light videos, achieving 11 fundamental cattle behavior recognitions through an enhanced SlowFast model (57fps real-time processing). Zheng *et al*. (2023) developed a Siam-AM dual-network architecture incorporating attention mechanisms for leg motion tracking, demonstrating 94.7% lameness detection accuracy across three large-scale farms. Gan *et al*. (2021) and Bati and Ser (2023) addressed social interactions in piglets and ovine stress responses respectively, with the former attaining F1=0.9377 for aggression detection in 8-hour videos using spatiotemporal CNN, while the latter implemented fear behavior classification through optical flow-CNN fusion. Yan *et al*. (2024) proposed a dual-modality network with adaptive RGB-optical flow fusion, achieving 77.8% recall for porcine aggression detection in 642 annotated clips. Gao *et al*. (2023)'s team enhanced the UD-YOLOv5s model *via* jaw skeleton feature extraction, reaching 86.4% mAP for rumination recognition.

Free-range breeding

In free-range breeding scenarios, livestock have a larger range of activity and a more natural growth environment and their Behavior and posture may be more diverse and diverse. Free-range livestock can exhibit more exploratory and active behaviors, such as foraging, playing, or communicating. By monitoring the Behavior and posture of free-range livestock, we can gain a more comprehensive understanding of their adaptability to the natural environment, as well as their personality traits and social behavior exhibited in free activities.

Kirsch *et al*. (2025) integrated Time-Distributed Residual LSTM-CNN with bidirectional LSTM to create a hierarchical framework for equine behavior classification (<93\% cross-validation accuracy across 15 activities). Gu *et al*. (2023)'s team developed a two-stage recognition system that preliminarily screens six sheep behaviors (including standing/attacking) before VGG network refinement, maintaining model memory under 120MB.

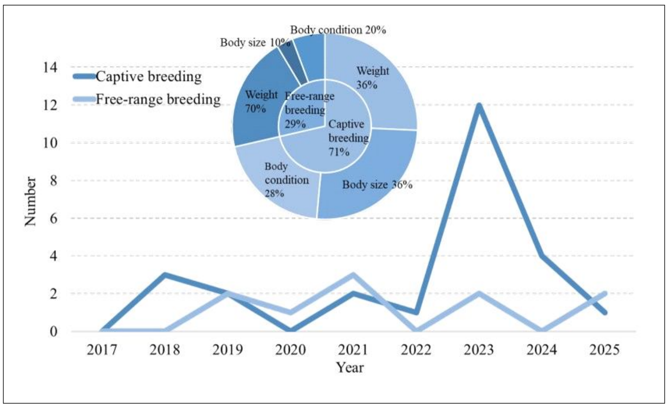

Fig 5: Comparison of growth estimation.

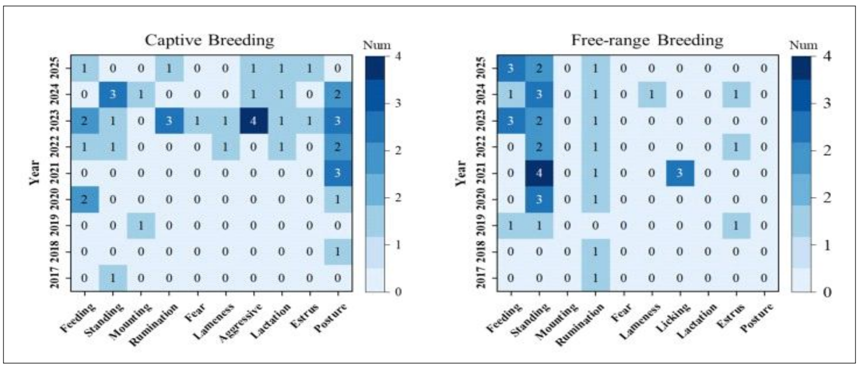

Fig 6: Behavior and posture papers from the last decade in captive breeding and free-range breeding.

Schmeling *et al*. (2021) and Li *et al*. (2024) devised multi-sensor solutions: the former predicted bovine lying patterns using accelerometer-magnetometer-gyroscope fusion, while the latter achieved 93.64% lameness detection accuracy in 330-cow trials through EfficientNet-B0-based hoof-angle analysis. Riaboff *et al*. (2020) revealed *via* accelerometer-GPS correlation that 63% rumination occurs under tree shade in permanent pastures, with feeding frequency increasing by 28% near automated milking systems in temporary grasslands.

Summary

In captive breeding, the limited range of animal activity allows for easier and more precise monitoring of behavior and posture. In contrast, free-range breeding is significantly influenced by natural conditions, requiring researchers to develop effective monitoring solutions for dynamic environments. As illustrated in Fig 6 the distribution of research on behavior and posture detection varies, with a greater emphasis on behaviors such as feeding and social interactions in free-range settings compared to controlled captive studies (Table 4 in the Appendix).

Technologically, the diversity of detection methods reflects adaptability to different scenarios. Captive breeding benefits from video analysis and deep learning models like YOLO for real-time posture analysis. In free-range contexts, automated sensors and cameras are increasingly used; for example, Gu *et al*. (2023) employed RGB-D cameras to monitor cattle behavior under variable conditions. Due to natural elements affecting data in free-range settings, integrating multiple sensors like accelerometers and GPS is crucial for improving accuracy.

Species-specific behavioral traits also influence the choice of posture detection technologies. Different species, such as pigs, cattle and sheep, require tailored approaches; for instance, Eisermann (2022) used jaw-tracking equipment measurements for pigs, while cattle behavior detection relies more on video analysis. This specialization enhances monitoring accuracy and efficiency, facilitating the development of tailored management strategies.

Prospects

Research on AI-based LHM has become a hot topic in academia. Literature analysis shows that in captive breeding, the focus is on high-precision visual recognition, behavior and posture monitoring, utilizing deep learning for accurate individual identification and anomaly detection. In contrast, free-range breeding emphasizes multi-sensor integration and environmental adaptability, using GPS, sensors and long-term dynamic monitoring to navigate complex natural environments. This research highlights the preference for static monitoring technologies in confined settings, while free-range contexts rely on integrated multi-source data, emphasizing system robustness and adaptability and presenting distinct technological strategies for each breeding scenario. We foresee significant advancements in the LHM domain

Table 4: Behavior and posture detection of livestock.

Scenarios	Reference	Space	MET	SC	EC	DC	Detection task	Performance
Free-range breeding	Simanungkalit *et al*. (2021)	Cattle	RFID and ACC	grazing	Na-env	Acceleration value	Licking	Efficiency: 98%
	Kirsch *et al*. (2025)	Horse	ActiGraph GT9X	Paddock	Na-env	Numeric TS	Trotting, Chewing...	Accuracy >93%
	Riaboff *et al*. (2020)	Cows	GPS, ACC	grazing	Na-env	Numeric TS	Posture, Rumination	Accuracy: 98%
	Li *et al*. (2024)	Cattle	ACC	grazing	Na-env	Numeric TS	Lameness	Accuracy: 93.64%
	Schmeling *et al*. (2021)	Cows	ACC, Magnometer	Pasture	Na-env	Numeric TS	Posture, Rumination	Accuracy: 87.4%
	Zia *et al*. (2023)	Cattle	Vidiction	Pasture	Na-env	Video recordings	Posture	mAP: 73.96%
Captive breeding	Wang *et al*. (2023)	Pig	Vidiction	Pen	Controlled	Images	Posture	mAP: 74.09%
	Zheng *et al*. (2023)	Cattle	Camera	Barn corridor	Na-env	Video sequence	Lameness	Accuracy: 94.73%
	Gan *et al*. (2021)	Pig	Camera	Pen	Controlled	Video sequence	Lactation	MAE: 96.7%
	Gao *et al*. (2023)	Pig	Vidiction	Pen	Controlled	Video sequence	Aggressive	Accuracy: 94.8%
	Shi *et al*. (2025)	Goat	Vidiction	Pen	Controlled	Video sequence	Estrus	Accuracy: 97.5%
	Gao *et al*. (2023)	Cattle	Vidiction	Ranch pen	Controlled	Images	Rumination	Accuracy: 98.25%
	Bati and Ser *et al*. (2023)	Sheep	Vidiction	Arena pen	Na-env	Video	Fear	H-accuracy: 100%
	Yan *et al*. (2024)	Pig	Vidiction	Pen	Controlled	Video	Aggressive	AP:68%, AR:77.8%

Footnote: MET=Monitoring equipment type, SC=Spatial characteristics, EC=Environmental controllability, DC=Data collection, NR: Not reported in the original paper, Na-env: Natural environment. "Controlled" means artificially controllable, for example: Light, temperature, humidity, *etc*.

regarding structure, content and technology, leading to new innovations in intelligent animal breeding.

Classification method

This study examines scenarios in LHM, distinguishing between free-range breeding and captive breeding. Health assessments of livestock in free-range environments help simulate natural ecosystems, enabling a holistic evaluation of their well-being. In contrast, monitoring in captive environments minimizes external influences, yielding more precise data. Future studies could explore different categorizations, such as classifying LHM research based on livestock husbandry purposes:

(1) **Meat-producing livestock:** Specifically bred for meat production.

(2) **Dairy livestock:** Primarily serving for milk and dairy product output, *e.g.*, cows, sheep.

(3) **Working livestock:** Utilized for tasks like plowing and transportation, *e.g.*, horses, cattle.

(4) **Fur-producing livestock:** Reared for fur or wool extraction.

Through this classification method, personalized improvements can be made to the health status of livestock and targeted management suggestions can be provided for various types of animal husbandry, promoting the development and health enhancement of the entire animal husbandry industry.

Enhance refined management

Captive breeding offers significant opportunities for improved livestock management, particularly in behavior and posture detection. Future research can focus on:

(1) **Diversified behavior detection**

Integrating multiplesensor technologies, such as video surveillance and accelerometers, to develop algorithms that recognize various postures and behaviors, aiding in early detection of health issues and enhancing animal welfare.

(2) **Behavior pattern analysis**

Utilizing machine learning to identify behavior patterns in livestock, creating databases and alert systems that help herders monitor health and status effectively.

In free-range breeding, there is untapped potential for precision management, as current research predominantly emphasizes high-accuracy recognition tasks while neglecting growth indicator detection. Future directions may include:

(1) Sensor technology

Integrating machine learning with sensors (like neck collars or RFID tags) to monitor body size and enable real-time weight tracking.

(2) Computer vision technology

Employing portable devices for monitoring livestock growth, using smartphones or cameras to capture images for analysis and weight estimation through deep learning.

(3) Intelligent devices

Developing tools to automatically record and transmit growth data to the cloud for precise analysis through AI algorithms.

Technological improvements

Remote monitoring and data-driven decision-making

Current AI-driven LHM research faces challenges with fragmented monitoring tasks, such as livestock identification, posture detection and weight measurements, leading to inefficiencies and information silos. Future research should focus on developing an integrated monitoring system to streamline these tasks, enhancing data accuracy and decision-making. This system will utilize sensor technologies and internet connectivity for real-time health monitoring, enabling farmers to access comprehensive physiological and environmental data anytime. Intelligent decision support systems powered by machine learning can analyze health trends, predict disease outbreaks and provide targeted advice, thus improving productivity while ensuring livestock health.

Multimodal data fusion and comprehensive assessment

Future LHM research should prioritize multimodal data fusion by integrating data from various sensors, such as images, videos and sounds, for a comprehensive health assessment. For example, analyzing both audio and visual data can help detect abnormal breathing sounds and infer potential health issues. This approach, combined with machine learning, can enhance diagnostic accuracy in livestock health assessment.

Enhancing model performance in low data sample scenarios

AI-empowered LHM research typically relies on large datasets for image processing and deep learning. However, the scarcity of publicly available livestock datasets and the absence of standard data formats hinder generalization across studies. Future research should explore enhancing model performance in low-sample scenarios through techniques like transfer learning, meta-learning and active learning to leverage existing data effectively. Furthermore, methods such as Generative Networks and self-supervised learning can augment datasets, improving diversity and robustness. Combining these advanced technologies will help develop more precise models for livestock health monitoring, addressing challenges related to limited sample data and pushing innovation in AI-empowered LHM technology.

CONCLUSION

This paper analyzes over 200 AI studies on LHM in captive and free-range breeding, focusing on three key tasks: livestock identification, growth estimation and behavior detection. It compares monitoring approaches in both scenarios, outlines current challenges in the LHM domain and suggests future research directions for more effective livestock management solutions.

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Conflict of interest

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