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Review Article

Non-contact technologies for cattle monitoring: advances and challenges towards precision livestock farming

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ABSTRACT

Precision livestock farming has become essential for sustainable production, animal welfare, and management efficiency. Non-contact monitoring technologies have emerged as promising solutions. Compared with wearable or invasive devices, non-contact approaches enable continuous and stable monitoring without disturbing natural behaviors, thereby minimizing stress and welfare risks. This review provides a comprehensive review of research progress on non-contact technologies in cattle farming, covering five core domains: individual identification, morphological trait assessment, behavioral analysis, vital signs monitoring, and disease detection. Furthermore, key bottlenecks hindering large-scale deployment are identified, and future development prospects are outlined across four dimensions: data resources, algorithmic performance, evaluation frameworks, and system integration. This review aims to foster interdisciplinary collaboration and technical advancement of non-contact technologies in precision cattle farming through systematic synthesis and critical discussion, offering valuable insights for both practical applications and future research.

1. Introduction

Livestock production constitutes a fundamental sector of global agriculture, supplying diverse animal-derived products including meat, dairy, eggs, wool, and leather. Among domesticated species, cattle hold a distinctive status within the livestock industry owing to their high economic value per individual and their extended growth and production periods (Qiao et al., 2021; Zhang et al., 2024a). Specifically, beef cattle typically reach market weight after approximately two years, whereas dairy cows may remain in production for more than a decade, which is substantially longer than other common livestock such as pigs, broilers, and layers (Albertí et al., 2008; De Vries and Marcondes, 2020;

Abbreviations: PLF, Precision Livestock Farming; SIFT, Scale-Invariant Feature Transform; SURF, Speeded-Up Robust Features; WLD, Weber Local Descriptor; LBP, Local Binary Patterns; EEM, Embedding Enhancement Module; EOM, Embedding Optimization Module; SNN, Siamese Neural Network; PDE, Phased Dynamic Expansion; CE, Cross-Entropy; CMC-1, Cumulative Matching Characteristic at Rank-1; LKA, Locate Key Area; BL, Body Length; BH, Body Height; HH, Hip Height; WH, Wither Height; CD, Chest Depth; HG, Heart Girth; AG, Abdominal Girth; SC, Shank Circumference; SfM, Structure from Motion; NeRF, Neural Radiance Fields; 3DGS, 3D Gaussian; SSM, Statistical Shape Model; EMA, Eye Muscle Area; MLR, Multiple Linear Regression; RL, Rump Length; MAPE, Mean Absolute Percentage Error; HL, Hip Length; GPR, Gaussian Process Regression; RMSE, Root Mean Square Error; BCS, Body Condition Score; MAE, Mean Absolute Error; LSTM, Long Short-Term Memory; FFT, Fast Fourier Transform; PCA, Principal Component Analysis; HMM, Hidden Markov Model; CD, Cumulative Euclidean Distance; CA, Cumulative Magnitude of Acceleration; CMA, Cumulative Moving Average of Triangle Area; IRT, Infrared Thermography; ROI, Region of Interest; RR, Respiration Rate; PBVM, Phase-Based Video Magnification; LK, Lucas-Kanade; FMCW, Frequency Modulated Continuous Wave; ECG, Electrocardiogram; rPPG, Remote photoplethysmography; MCG, Magnetocardiography; SCC, Somatic Cell Count; CMT, California Mastitis Test; AMS, Automatic Milking Systems; HERD, Holistic Explainable Referential Datahub.

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Hu et al., 2021). Maintaining cattle health and stable growth throughout the production cycle is essential for both economic efficiency and animal welfare, helping to prevent premature culling caused by digestive, respiratory, metabolic, locomotor, or reproductive disorders (Olechnowicz and Jaśkowski, 2011; Chiumia et al., 2012; Robcis et al., 2023). In conventional cattle farms, herd management typically relies on manual observation of individual animals and decision-making guided by the farmer's experience. This approach is labor-intensive, time-consuming, and inherently subjective. Such subjectivity may delay the timely detection of critical reproductive and health events, leading to measurable economic consequences. For example, reduced estrus detection efficiency has been shown to increase days open, resulting in economic losses of roughly $0.7-$5 per additional days open per cow (Louca, 1968; de Vires, 2006; Krpálková et al., 2020; Temesgen et al., 2022). Similarly, delayed lameness detection may prolong disease duration, with modeling studies estimating additional losses of approximately $13 per week of lameness persistence (Robcis et al., 2023). In recent years, intensive rearing has been promoted in many countries to reconcile the gap between limited productivity and rising market demand (Manzoor et al., 2023). However, with the continuous expansion of cattle farm size, individual animals receive progressively less attention, rendering precise and individualized monitoring increasingly challenging (Shen et al., 2021; Xu et al., 2024a; Moe et al., 2025). Consequently, the development and exploration of advanced technologies and approaches to modernize the cattle industry are urgently required.

Precision Livestock Farming (PLF) has been widely acknowledged as an effective approach to tackle the challenges confronting the livestock industry (Wathes et al., 2008; Norton et al., 2019; Neethirajan and Kemp, 2021). It leverages advanced technologies to achieve accurate perception of animal states at the individual level, thereby enabling precise feedback and supporting data-driven management decisions. As illustrated in Fig. 1, intelligent information perception serves as a bridge and support between cattle well-being and farmers' management decision-making.

In recent years, wearable and implantable devices (e.g. neck collars, ear tags, and embedded sensors) have been applied to monitor cattle behavior and physiological states. Although these devices have facilitated the progress of PLF, their use remains limited by concerns regarding animal welfare, equipment cost, and durability (Qiao et al., 2021; Rahman et al., 2025). In contrast, non-contact technologies are a subset of non-invasive methods that monitor animals without any physical contact, distinguishing them from wearable or implantable devices and thereby minimizing animal handling (Wang et al., 2025d). They provide cost-efficient, scalable, and continuous monitoring solutions and are increasingly recognized as a promising pathway for advancing precision livestock management.

Although non-contact monitoring technologies have developed rapidly in cattle farming and shown great application potential, a comprehensive review that systematically defines monitoring tasks, outlines the challenges they face, and examines the current state of technological solutions remains absent. Addressing this gap is expected to clarify the strengths and limitations of existing approaches, guide future research directions, and facilitate the adoption of these technologies in real-world farming environments. It is worth noting that several existing reviews address themes similar to those of this study but differ in emphasis. Mahmud et al. (2021) and Rahman et al. (2025) examined deep learning–based studies in precision cattle or livestock farming, focusing on data acquisition and network architecture design. Qiao et al. (2021) summarized advances in cattle identification, body condition scoring, and live-weight estimation, without concentrating on non-contact approaches. Yin et al. (2023) reviewed non-contact sensing technologies in livestock and poultry production from the perspective of sensing modalities, including infrared, microwave, imaging, and acoustic sensors. In contrast to previous reviews, this work adopted a task-oriented perspective, encompassing core areas including individual identification, morphological trait assessment, behavioral analysis, vital signs monitoring, and disease detection. The literature search was conducted across multiple databases (e.g., Web of Science, Scopus, PubMed), and all literature included in this review was retrieved up to February 1, 2026. Each area was thoroughly analyzed and summarized to provide a comprehensive overview of non-contact monitoring technologies in cattle production, serving as a reference for future research and practical applications.

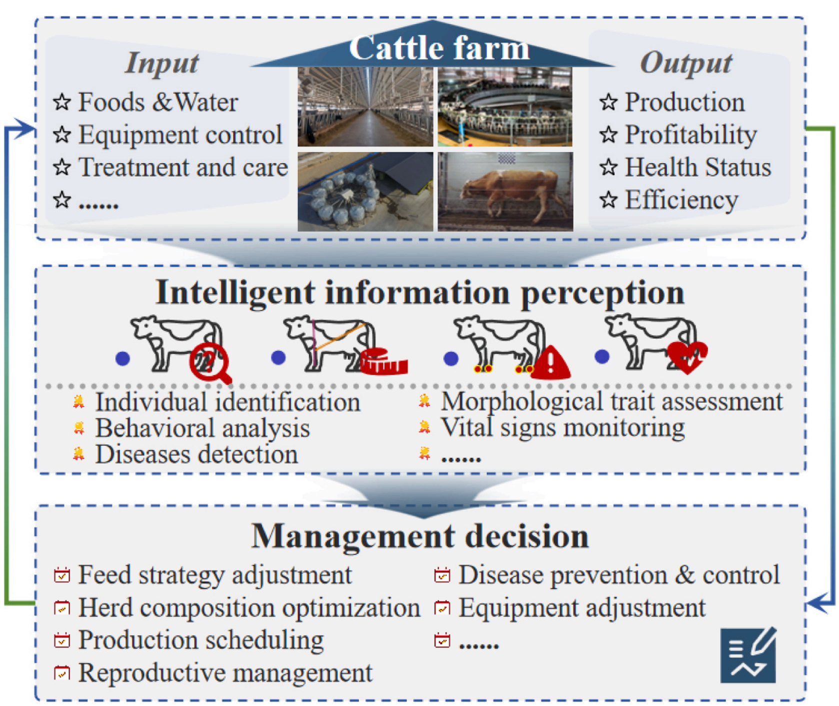


Fig. 1. System framework of precision livestock farming.

2. Cattle identification

Accurate acquisition of individual identity information is essential to precision cattle farming, as monitoring data (e.g. body size, weight, and feed intake) can only be effectively recorded and utilized when precisely associated with each individual (Hossain et al., 2022; Kaur et al., 2022; Xu et al., 2025c). In addition, as illustrated in Fig. 2, a reliable identification system generates benefits for multiple stakeholders.

Apart from cattle themselves and farm managers as the most direct beneficiaries, some participants or institutions such as dairy consumers, insurance companies, banks, and governments also benefit from advancements in cattle identification technologies (Qiao et al., 2021; Xu et al., 2024a; Menezes et al., 2025). Therefore, individual identification technology serves not only as a practical tool for daily herd management but also as a cornerstone in promoting the intelligent transformation of modern livestock production.

Compared with contact or invasive methods such as plastic or RFID ear tags, non-contact identification is based on the animal's intrinsic biological characteristics instead of externally designed attachments (Hossain et al., 2022; Sharma et al., 2025). This field has advanced rapidly in recent years. As illustrated in Fig. 3, common identification targets include the retinal, muzzle pattern, face, and body trunk. Each biometric feature differs in accessibility, precision, and suitability, and faces unique technical challenges.

2.1. Retinal and muzzle-based identification

Retina and muzzle patterns exhibit high biological uniqueness and remain largely unchanged during growth (Allen et al., 2008). Retinal features consist of unique patterns formed by the vascular network at the back of the eye. Muzzle patterns are characterized by distinctive arrangements of beads and ridges on the nose.

Historically, identification relied on handcrafted local descriptors. Techniques such as Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Weber Local Descriptor (WLD), and Local Binary Patterns (LBP) were widely employed to extract featrues. In the context of muzzle recognition, to enhance robustness against rotation and scaling, Awad et al. (2013) integrated RANSAC with SIFT, attaining 93.3% accuracy. Similarly, Kusakunniran et al. (2020) combined BoHoG with LBP, maintaining an accuracy of 95%. Parallel efforts were made in retinal identification; for instance, Saygili et al. (2024) applied the SURF operator following image enhancement and segmentation operations, achieving an accuracy of 92.25%.

To address the limitations of aforementioned methods in robustness and generalization, deep learning approaches have been adopted for identity feature extraction. CNN-based architectures have become the standard solution for robust feature extraction. In retinal identification, Cíhan et al. (2025a) developed a U-net-based system to precisely segment vascular patterns, achieving an identification accuracy of 97.4%. Similarly, for muzzle patterns, CNN models have consistently pushed identification accuracies above 97% by automatically extracting highly discriminative features (Bello et al., 2021; Shojaeipour et al., 2021; Li et al., 2022a). In addition to convolutional models, Transformer architectures have also demonstrated strong potential. For instance, Kumar and Singh (2026) introduced a multi-directional patch encoding approach to capture global dependencies, attaining a competitive accuracy of 97.8%.

Although these methods demonstrate satisfactory accuracy, the challenges of data acquisition significantly restrict their applicability. Image capture typically requires controlled conditions, with animals remaining still and cooperative rather than moving naturally. Moreover, retinal images generally necessitate professional fundus, while muzzle images are prone to blurring or occlusion due to sweat, feed residues, or dirt (Pathak and Parakash, 2026). Therefore, these approaches are more suitable for specialized applications that demand high accuracy in individual identification, such as breeding record documentation or high-value cattle transactions, and are of relatively limited feasibility for high-throughput information collection in routine precision livestock management.

2.2. Face-based identification

Cattle facial features encompass the morphology of the eyes, mouth, nose, and ears, along with coat color patterns and skin textures, exhibiting considerable individual variation (Kim et al., 2005b; Bergman et al., 2024; Mahato and Neethirajan, 2025). Unlike retinal or muzzle patterns that require strictly controlled acquisition, facial images can be obtained in relatively natural farming environments, such as during feeding or milking, making them more suitable for routine livestock management (Weng et al., 2022; Xu et al., 2025c). However, deploying facial recognition to real-world applications introduces three critical challenges: robustness under unconstrained conditions, efficiency on resource-limited devices, and adaptability to data-scarce regimes.

Addressing robustness under unconstrained conditions constitutes the primary research focus. A major challenge arises from pose variation. To mitigate this, capturing multi-angle images has been explored as a effective strategy to acquire comprehensive facial information (Bergamini et al., 2018; Weng et al., 2022). For instance, Weng et al. (2022) developed a Two-Branch CNN that explicitly integrates features from two images captured at different angles, thereby enriching the

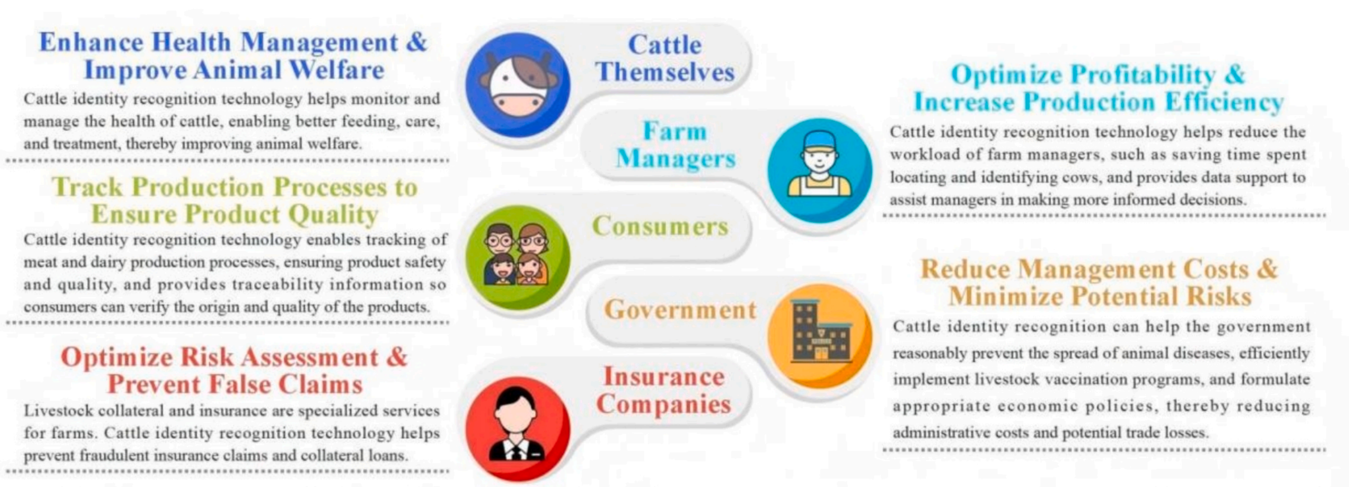


Fig. 2. Beneficiaries of the cattle identity recognition method.

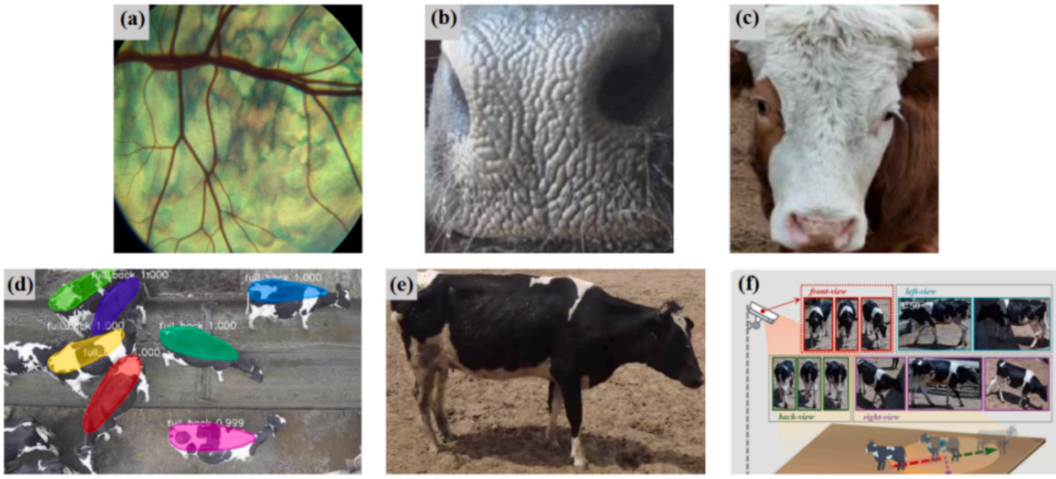


Fig. 3. Biometric features used for identifying cattle. (a) Retinal (Saygili et al., 2024); (b) Muzzle (Kumar et al., 2018);(c) Face (Weng et al., 2022);(d) Top-view trunk (Xiao et al., 2022); (e) Side-view trunk (Wang et al., 2024e); (f) Random perspective trunk (Xu et al., 2025a).

input representation. Conversely, considering the logistical complexity and hardware costs of acquiring multi-angle imagery, considerable research has focused on addressing scenarios limited to single-view capture. In this context, explicit geometric alignment, achieved by detecting key landmarks (e.g., eyes, nose) for rotation correction, has proven effective in normalizing head orientations (Yang et al., 2024a; Han et al., 2025a). Beyond explicit alignment, robustness can also be enhanced at the feature embedding level. For instance, Xu et al. (2024a) proposed an Embedding Optimization Module (EOM) that aggregates diverse pose features into "pose-irrelevant" sub-centers, ensuring that profile views cluster tightly with frontal views without requiring pre-processing steps. Beyond pose variation, identification accuracy is also frequently compromised by physical occlusions (e.g., feed residues), illumination fluctuations, and other environmental disturbances (Mahato and Neethirajan, 2025). To address these challenges, Hu et al. (2025) proposed AngusRecNet, which integrates asymmetric convolutions and a specialized attention mechanism to compensate for occluded regions by leveraging contextual information and refining features from non-occluded areas. Similarly, Pathak and Parakash (2026) enhanced robustness through fine-grained analysis, fusing weighted local part-level features with global representations to ensure reliability even when specific facial regions are compromised.

Beyond accuracy, model efficiency is a decisive factor for deployment on hardware with limited computational resources. To navigate the trade-off between performance and complexity, research has increasingly adopted lightweight architecture design. A prominent strategy involves leveraging established mobile backbones, as demonstrated by (Xu et al., 2022), who utilized MobileNet combined with ArcFace loss to significantly reduce model size while maintaining high recognition accuracy. Extending this to system-level integration, Chen et al. (2025b) validated the practicality of MobileNet within an IoT framework, enabling real-time monitoring of feeding behavior on edge devices. Pushing this boundary further towards ultra-compact designs, Li et al. (2022b) developed a custom CNN with as few as 0.17 M parameters and 9.17 MFLOPs. This model achieved 98.37% accuracy with millisecond-level latency on a Raspberry Pi, showcasing the potential for extreme efficiency in edge deployment.

Adaptability to data-scarce regimes and dynamic herd changes constitutes another critical barrier. Given that collecting large-scale labeled datasets for every individual farm is impractical, few-shot learning approaches have emerged as key solutions. Prominent approaches include Siamese Neural Networks (SNN) (Bakhshayeshi et al., 2023) and *meta*-learning frameworks (Xu et al., 2025c), both of which significantly reduce data dependency, achieving high accuracy with only 5–20 samples per cow. However, beyond static data scarcity, practical systems must also accommodate herd dynamics. To address new births or purchases without catastrophic forgetting, incremental learning strategies like Phased Dynamic Expansion (PDE) have been proposed. By preserving old knowledge via distillation, this approach maintains high accuracy (<1.5% drop) while eliminating the need for costly retraining (Weng et al., 2025).

2.3. Trunk-based identification

Cattle trunk characteristics, including body contour, coat pattern distribution, and skin texture, exhibit individual variation and can be applied for identity recognition. Compared with features such as the retinal, muzzle, or facial region, trunk characteristics can be captured from standard surveillance viewpoints without requiring close-up interaction (Bakhshayeshi et al., 2023; Lu et al., 2023; Menezes et al., 2025). This field has witnessed rapid development in recent years. Driven by the demand for flexible deployment in practical scenarios, these advancements can be characterized as a continuous evolutionary journey, transitioning from fixed-view capture in controlled passageways to random-view identification in unconstrained environments.

Early implementations prioritized image stability by constraining animal movement. Systems were typically deployed in narrow passageways to capture standardized top-down or side views of individual cows passing sequentially. Kim et al. (2005a) first verified the feasibility of this concept using binary images of coat patterns. Following this, subsequent studies utilized fixed cameras to capture specific body regions, such as the back (Ferreira et al., 2022; Wang et al., 2024b; Menezes et al., 2025), rump (Li et al., 2017), or lateral trunk (Zhao et al., 2019; Achour et al., 2020; Hu et al., 2020; Bhole et al., 2022). However, the reliance on specific facility structures (e.g., milking parlors or weighing chutes) limits the scope of daily monitoring, as animals not involved in routine handling (e.g., dry cows or free-ranging cattle) may not pass through these checkpoints regularly.

Exploring diverse avenues to broaden identification applicability remains a key objective. Unlike traditional methods restricted to standing animals, Xiao et al. (2024) pioneered a framework capable of identifying lying cows, addressing a critical need for welfare monitoring. Beyond posture, breed adaptability presents a distinct challenge. Since breeds like Jersey or Wagyu lack distinctive coat patterns, texture-based methods often fail. To overcome this, research has shifted towards texture-independent biometrics, leveraging depth information to capture 3D body contours (Sharma et al., 2025) or keypoint-based approaches that utilize anatomical landmarks (Menezes et al., 2025). At the system level, robust frameworks have been established to accommodate dynamic herd management. Wang et al. (2024b) developed

LightCowsNet for open-set recognition, while Wang et al. (2025c) proposed a systematic "best practice" framework, validating these advancements across multi-platform datasets.

Ensuring robustness under random viewpoints constitutes a critical frontier. In free-stall barns, non-rigid body deformations and complex backgrounds create significant interference. To mitigate this, researchers have focused on refining feature discriminability via loss functions and guiding feature extraction via attention mechanisms. Regarding loss formulation, efforts have evolved from optimizing standard metric learning objectives to designing specific losses. For instance, strategies like Compact Loss and Triplet Loss have been employed to enhance feature compactness and training stability (Zhao and Lian, 2022; Wang et al., 2023b). Taking this further, novel objectives such as Central Momentum Contrast loss have been specifically tailored to address the asymmetry of coat patterns, achieving Rank-1 accuracies up to 99.50% (Wang et al., 2024e). Simultaneously, structural innovations focus on guiding models to salient regions. Hao et al. (2023) integrated multiple attention modules to jointly model spatial and channel dependencies, achieving 98.91% accuracy. Similarly, Lu et al. (2023) developed a Locate Key Area (LKA) module to automatically crop discriminative regions without manual annotation. Notably, Xu et al. (2024c) combined attention mechanisms with counterfactual learning to assess feature reliability, enabling the model to learn global representations resilient to viewpoint changes.

Collectively, these studies indicate that different biometric features present distinct trade-offs. Retinal and muzzle patterns provide high identification precision but require controlled acquisition conditions, whereas facial and trunk features offer superior accessibility and are more suitable for routine farm environments, albeit with increased sensitivity to occlusion, viewpoint variation, and environmental interference. Building on the preceding analysis and the insights presented in Table 1, the field of non-contact cattle identification has advanced rapidly. Driven by the strong representation capability of deep learning, research has transitioned from idealized settings toward practical deployment in real farming environments. A central challenge in practical applications is animal re-identification, which requires consistently tracking the same individual across different times or camera views in a herd, particularly in large-scale farms where maintaining identity continuity is essential for reliable behavior, health, and productivity monitoring. Accordingly, recent studies increasingly emphasize robustness under random viewpoints, adaptability to open-set conditions, feasibility in data-scarce regimes, and generalization across solid-colored breeds.

3. Morphological trait assessment

Body measurements, body weight, and body condition, along with their dynamic changes, are important indicators for evaluating growth, health status, reproductive ability, and production performance of cattle (Wildman et al., 1982; Krogstad and Bradford, 2025). They also provide guidance for livestock management, breed selection, and productivity improvement (Li et al., 2025a; Zhou et al., 2025). Notably, these indicators differ in their temporal responsiveness and management roles, which influences how they are interpreted and utilized in practical decision-making. Under large-scale farming conditions, achieving frequent and continuous monitoring of these indicators has become a significant challenge for farm management (Swartz et al., 2025). Non-contact monitoring technologies provide a new solution and have become a core component supporting PLF.

3.1. Body size measurement

Common body measurement indicators are illustrated in Fig. 4. The first type includes linear measurements, such as Body Length (BL), Body Height (BH), Hip Height (HH), Wither Height (WH), and Chest Depth (CD), which represent straight-line distances between key anatomical points. The second type includes curved measurements, such as Heart Girth (HG), Abdominal Girth (AG), and Shank Circumference (SC), which correspond to the circumference of specific body regions. Each indicator holds distinct significance in farming and breeding (Heinrichs et al., 1992). For instance, BL and BH reflect body size and growth development. HH serves as an important reference for maturity and body structure. CG is closely related to body weight and milk yield. SC indicates limb bone mass and overall body robustness.

Table 2 summarizes several representative studies on body measurements. Synthesizing these works, the technical evolution centers on two core axes: phenotypic data acquisition and key point localization.

Accurate phenotypic data acquisition is fundamental prerequisite for precise body measurements (Le Cozler et al., 2019b; Yang et al., 2023). Regarding acquisition devices, 2D cameras based on CCD or CMOS sensors are widely adopted due to their cost-effectiveness and scalability in large farms. However, they lack direct spatial depth information and typically require multi-camera setups, dedicated reconstruction algorithms, and careful calibration to approximate three-dimensional structure, which may limit accuracy in volumetric or body weight estimation. In contrast, three-dimensional sensors, such as depth cameras and LiDAR, are widely used to capture real spatial scale information. LiDAR provides high-precision point clouds with superior data quality, but its high cost and large data volume hinder real-time deployment (Li et al., 2025b). Structured-light-based depth cameras are highly sensitive to illumination, limiting their outdoor applicability. Time-of-flight (ToF) depth cameras, such as Kinect v2 and Kinect DK, and stereo vision-based depth cameras, such as ZED 2i, are the most commonly applied in practice (Devi et al., 2024; Deng et al., 2025; Lu et al., 2025; Zhou et al., 2025). Regarding acquisition methods, common deployment modes include arch-type, channel-type, and mobile-type (Fig. 5), which mainly differ depending on the sensor quantity, performance, and application requirements. Arch-type acquisition typically employs multiple 3D sensors, which must be calibrated for extrinsic parameters and synchronized. This approach provides comprehensive point cloud coverage and is suitable for complex 3D analysis (Zhou et al., 2025). However, it generally requires fixed or dedicated sites, limiting flexibility and increasing hardware costs. Channel-type acquisition uses a single 3D device installed at the side or above the channel. This approach typically captures point clouds from only one side. While data processing is simpler than in the arch-type setup, the extractable phenotypic information remains limited, and measurements such as HG and AG are consequently difficult to obtain (Zhang et al., 2024b; Hou et al., 2025; Yang et al., 2025). Mobile-type acquisition captures multiple 2D images and reconstructs point clouds via Structure from Motion (SfM), Neural Radiance Fields (NeRF), or 3D Gaussian (3DGS) methods, followed by subsequent body measurement steps (Yang et al., 2022; Yang et al., 2023; Jing et al., 2025). This approach generally requires stationary cattle, which is difficult to ensure in real farm conditions. Therefore, the selection of acquisition devices and methods must be carefully balanced according to specific farming scenarios and research objectives.

Accurate localization of measurement points is regarded as a critical step in the measurement process (Deng et al., 2025; Zhou et al., 2025). To enhance measurement accuracy, attention has been focused on achieving efficient and precise key point detection after data acquisition. Early approaches relied on manual annotation, where specialists labeled key points in point cloud data individually (Salau et al., 2017; Le Cozler et al., 2019a; Le Cozler et al., 2019b). This process was time-consuming and labor-intensive, limiting its applicability in large-scale farming. One transitional approach used markers attached to the cattle surface to assist algorithms in spatial key point localization (Ruchay et al., 2020), but the method was ineffective for unmarked individuals, limiting its generalizability. To promote measurement automation some studies proposed key point localization approaches based on morphological features. These methods estimate key point positions from cattle morphology using curvature calculation, clustering, or polynomial fitting, achieving preliminary automation (Yang et al., 2022). However,

Table 1
Summary of studies on non-contact cattle identification based on different biometric features.

Biometric	Primary objective	Key focus	Research	Feature	Methodology or algorithm	Cattle No.	Dataset size	Performance	
Muzzle-based	Handcrafted features	Robust matching	(Awad et al., 2013)	RGB	SIFT and RANSAC	15	105	Accuracy	93.30%
		Feature robustness	(Kusakunniran et al., 2020)	RGB	BoHoG and LBP	N/S	431	Accuracy	95.00%
	Feature learning	Automated extraction	(Bello et al., 2021)	RGB	CNN variant	400	N/S	Accuracy	98.99%
			(Shojaeipour et al., 2021)	RGB	CNN variant	300	2,900	Accuracy	99.11%
			(Li et al., 2022a)	RGB	CNN variant	268	4,923	Accuracy	98.70%
			(Kumar and Singh, 2026)	RGB	ViT variant	50	–	Accuracy	97.80%
Retinal-based	Handcrafted feature	Image enhancement	(Saygili et al., 2024)	RGB	Improved SURF	300	2,430	Accuracy	92.25%
	Feature learning	Retinal segmentation	(Cihan et al., 2025b)	RGB	U-net based system	80	560	Accuracy	97.40%
Facial-based	Early exploration	Feasibility study	(Kim et al., 2005b)	RGB	Neural network	12	N/S	Accuracy	100%
	Robustness enhancement	Pose variation	(Weng et al., 2022)	RGB	Dual-branch CNN	130	18,200	Accuracy	99.71%
			(Yang et al., 2024a)	RGB	Rotation correction	110	2,376	Accuracy	83.60%
			(Han et al., 2025a)	RGB	Rotation correction	17	27,000	Accuracy	98.00%
			(Xu et al., 2024a)	RGB	Embedding optimization	118	10,137	Accuracy	98.69%
			(Pathak and Parakash, 2026)	RGB	Local-Global fusion	300	2,632	Accuracy	99.47%
	Model efficiency	Lightweight modeling	(Xu et al., 2022)	RGB	CattleFaceNet	Tr: 72 / Te: 9	2318	Accuracy	91.30%
			(Li et al., 2022b)	RGB	Lightweight CNN	103	10,239	Accuracy ParamsMFLOPs	98.37% 0.179.17
		IoT integration	(Chen et al., 2025b)	RGB	MobileNet v2	19	5,700	Accuracy	97.00%
	Sample efficiency	Few-shot learning	(Bakhshayeshi et al., 2023)	RGB	YOLO v5 and SNN	50	2,500	Accuracy	95.13%
			(Xu et al., 2025c)	RGB	Meta-learning	Tr: 195 / Te: 24	33,019	Accuracy	90.43%
		Incremental learning	(Weng et al., 2025)	RGB	Phased dynamic expansion	214	22,163	Accuracy	≈99%
Trunk-based	Early exploration	Feasibility study	(Kim et al., 2005a)	Binary image	Neural network	49	N/S	N/S	
	Fixed viewpoint	Back	(Ferreira et al., 2022)	Depth	VoxNet	38	5,697	F1 scores	0.939
			(Xiao et al., 2022)	RGB	Improved Mask R-CNN and SVM	48	12,000	Accuracy	98.67%
		Rump	(Li et al., 2017)	RGB	Zernike moments and QDA	10	1,965	Accuracy F1 scores	99.70% 0.995
		Lateral trunk	(Zhao et al., 2019)	RGB	FAST, SIFT and FLANN	66	528	Accuracy	96.72%
			(Achour et al., 2020)	RGB	CNN variant	17	4875	Accuracy	97.06%
			(Hu et al., 2020)	RGB	three CNNs and SVM	93	958	Accuracy	98.36%
			(Bhole et al., 2022)	RGB + Contour	DenseNet121 FC	383	3,694	Accuracy	99.64%
	Broader applicability	Open-set recognition	(Wang et al., 2024b)	RGB	LightCowsNet	Tr: 435/ Te: 181	32,020	mAP50:	94.26%
		Color-independent	(Sharma et al., 2025)	Point	PointNet	99	21,490	Accuracy	99.36%
			(Menezes et al., 2025)	RGB	Keypoint prediction and Siamese neural networks	41	25,712	Accuracy F1 scores	76.10% 0.792
		Lying posture	(Xiao et al., 2024)	RGB	YOLOX and CowbodyNet	72	4358	Accuracy	94.43%
	Random viewpoints	Training strategy	(Zhao and Lian, 2022)	RGB	Compact loss	Tr: 75 / Te: 25	4,073	Accuracy	97.86%
			(Wang et al., 2023b)	RGB	Triplet loss and Cross-Entropy loss	Tr: 70 / Te: 17	4,064	CMC-1mAP	94.12% 73.30%
			(Wang et al., 2024e)	RGB	Central Momentum Contrast loss	Tr: 70 / Te: 17	4,064	CMC-1mAP	99.50% 77.90%
		Model structure	(Hao et al., 2023)	RGB	Attention modules	227	37,011	Accuracy	98.91%
			(Lu et al., 2023)	RGB	Locate key area	41	10,608	Accuracy	99.11%
			(Xu et al., 2024b)	RGB	BoTNet and Counterfactual learning	84	907	Rank-1 Rank-5mAP	96.8% 98.9% 97.0%

Note: N/S = Not Specified. Tr / Te denotes the identity count in Training/Testing sets, indicating an open-set protocol (i.e., the testing identities were unseen during training). Entries without specific 'Tr/Te' notation imply a closed-set setting.

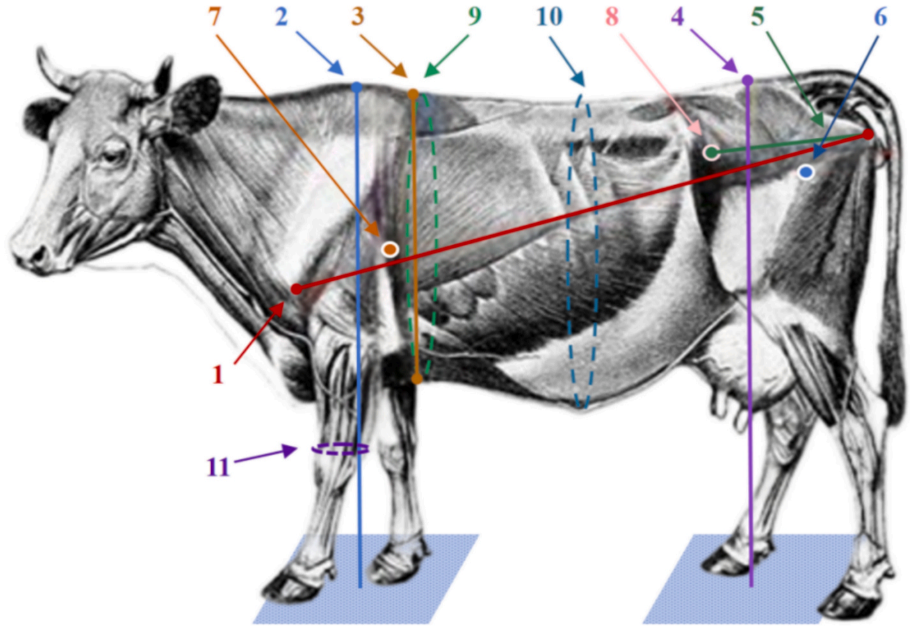


Fig. 4. Schematic diagram of cattle body size. (1) Oblique body length; (2) Body height; (3) Chest depth; (4) Hip height; (5) Hip height; (6) Hip width; (7) Chest width; (8) Ilium width; (9) Heard girth; (10) Abdominal girth; (11) Shank circumference.

these approaches are highly sensitive to parameter settings, resulting in limited stability and robustness. Other studies adopted part segmentation strategies, indirectly identifying measurement points by dividing different body regions (Hou et al., 2025; Zhou et al., 2025). For instance, Zhou et al. (2025) developed the FGPointKAN + point cloud segmentation model, which performs pixel-level division of cattle point clouds and determines key cutting planes and measurement points from the segmentation results. Recently, some researchers focused on fully automated key point localization to reduce manual effort and cumulative errors. One category of methods directly regresses key point coordinates in 3D point clouds (Xu et al., 2025d). Another category combines 2D RGB images with depth data, using deep learning to detect key points in RGB images first and then projecting them into 3D space for measurement (Deng et al., 2025; Yang et al., 2025). Although effective, these approaches are relatively sensitive to data noise. To address this, some studies have introduced Statistical Shape Model (SSM)-based methods. In these methods, the acquired data are fitted to a template mesh under constraints such as key points, and body measurements are then extracted from the normalized mesh (Luo et al., 2022; Bao et al., 2023; Luo et al., 2023; Wang et al., 2026). These approaches generally provide higher robustness and accuracy, but the iterative fitting process can be computationally demanding. Overall, key point localization techniques have evolved from manual annotation to geometric inference and now to deep learning-based methods, moving toward more efficient, robust, and generalizable automated solutions.

Drawing from the above discussion and Table 2, current research primarily centers on optimization in phenotypic data acquisition and breakthroughs in measurement point localization, converging towards efficient and automated solutions. Regarding data acquisition, cost-effective depth cameras (ToF, Stereo vision) have emerged as the preferred empirical choice, balancing hardware costs with sufficient precision for large-scale deployment. Simultaneously, in measurement methodology, deep learning-driven frameworks are replacing traditional geometric inference or manual annotation. Future research frontiers must therefore prioritize rationalizing sensor configurations for cost-efficiency, transitioning from rigid infrastructure to flexible, unconstrained monitoring, and ensuring algorithmic robustness against complex environmental interferences.

3.2. Body weight estimation

Weighbridges remain the standard approach for obtaining accurate cattle body weight. However, this method is infrequently utilized in practical farming as it demands additional equipment and requires animal restraint, making the process labor-intensive and stressful (Bhujel et al., 2025). Consequently, considerable research has focused on predicting body weight from body size. While simplified tools and empirical formulas, including the Weigh Tape, Rondo Tape, Schaeffer's Formula, and Agarwal's Formula, have been developed to address this issue (Heinrichs et al., 1992; Franco et al., 2017; Wangchuk et al., 2018). However, although these approaches partly alleviate the labor intensity of manual weighing, they remain dependent on human measurements and exhibit limited accuracy. With the rapid advancement of computer vision and related phenotypic perception technologies, it has become feasible to capture more comprehensive morphometric and phenotypic information from cattle, thereby establishing a solid foundation for non-contact, automated, and high-precision body weight estimation.

Table 3 summarizes representative studies on cattle body weight estimation. As illustrated, the prevailing methodology follows a two-stage framework: intermediate feature extraction followed by body weight regression.

In the first stage, intermediate parametric features are derived from 2D or 3D data using morphology-based or deep learning methods. These features primarily encompass morphometric traits with explicit biological meanings (e.g., BL, WH, HG). Considering that simple body size parameters fail to fully capture the complex 3D conformation of cattle, some research has incorporated volumetric and high-dimensional shape descriptors, providing a richer representation of body conformation. For instance, Le Cozler et al. (2019b) demonstrated that supplementing basic measurements with projected area and surface volume significantly enhanced regression accuracy. Similarly, Nir et al. (2018) and Weber et al. (2020) employed advanced geometric analysis, such as ellipse fitting and convex hull modeling, to extract sophisticated attributes like curvature and Hu moments, which effectively capture subtle morphological variations often missed by linear metrics. This trend towards localized feature representation is further exemplified by Peng et al. (2024), whose segment-based area features provided a more comprehensive characterization of body conformation than global

Table 2
Summary of studies on cattle body measurement.

Research	Breed	Collection setup	Device	Keypoint/landmark detection method	Measured traits	Performance
(Salau et al., 2017)	Holstein	Arch type	4 × Kinect v1	Manual annotation	Height of ischial tuberosity, front teat length	The standard errors of the ischial tuberosity were 0.7–1.5 mm for length and 2.4–4.0 mm for height.
(Le Cozler et al., 2019a)	Holstein	Arch type	5 × Morpho3D	Manual annotation	Chest depth, hip width, heart girth, backside width, ischial width, wither height	Correlations between manual and Morpho3D measurements were 0.89, 0.82, 0.78, 0.76, 0.63, 0.62, respectively
(Ruchay et al., 2020)	Hereford	Channel type	3 × Kinect v2	Manual annotation	Withers height, hip height, chest depth, heart girth, ilium width, hip width	With a 90% confidence level, measurement errors less than 3%
(Du et al., 2022)	Hereford	Channel type	3 × Kinect v2	2D keypoints detection projected to 3D	Withers height, hip height, chest width, ilium width, hip joint width, chest depth, heart girth, oblique body length, hip length	MAPE were 4.62%, 5.21%, 25.66%, 20.63%, 18.19%, 7.39%, 7.94%, 9.33%, and 16.39%, respectively
(Yang et al., 2022)	Holstein	Mobile type	Mobile phone	Morphology-based method	Withers height, body length, chest girth, and chest width	Average relative errors were 2.41%, 3.18%, 4.37%, and 6.12%, respectively
(Luo et al., 2022)	Hereford	Channel type	3 × Kinect v2	Statistical shape model-based method	Chest depth, ilium width, heart girth, oblique body length	MAPE were 9.26%, 8.85%, 10.14%, and 6.16%, respectively
(Bao et al., 2023)	Hereford	Channel type	3 × Kinect v2	Statistical shape model-based method	Chest width, ilium width, hip joint width, oblique body length, hip length, withers height, hip height, heart girth, chest depth	MAPE were 9.59%, 10.97%, 11.61%, 13.15%, 11.86%, 12.61%, 7.83%, 5.21%, and 9.60%, respectively
(Luo et al., 2023)	Hereford	Channel type	3 × Kinect v2	Statistical shape model-based method	withers height, hip height, chest depth, chest width, ilium width, hip joint width, oblique body length, hip length, heart girth	MAPE were 4.68%, 4.17%, 8.36%, 10.98%, 8.30%, 14.08%, 5.27%, 10.04%, and 6.60%, respectively
(Li et al., 2023a)	Simmental, Swiss brown	Arch type	5 × Kinect DK	Morphology-based method	Oblique body length, withers height, hip height, chest girth, abdominal girth	Average relative errors were 1.14%, 1.84%, 3.47%, 1.56%, and 2.36%, respectively
(Li et al., 2024e)	Simmental	Channel type	2D camera	Monocular depth estimation + 2D keypoints detection projected to 3D	Body height, oblique body length, chest depth, hoof diameter	Average relative errors were 6.75%, 7.55%, 8.00%, and 8.97%, respectively
(Zhang et al., 2024b)	Beef	Channel type	1 × IFM O3D303 LiDAR	Morphology-based polynomial fitting	Body height, abdominal height, withers height, chest girth, body length	MAPE were 5.17%, 4.85%, 3.49%, 6.54%, and 7.06%, respectively
(Deng et al., 2025)	Holstein, Qinchuan	Channel type	1 × ZED 2i	2D keypoints detection projected to 3D	Body length, body height, hip height, rump length	Maximum measurement deviations were 4.55%, 4.87%, 4.99%, and 6.76%, respectively
(Yang et al., 2025)	Holstein	Channel type	1 × ZED 2i	2D keypoints detection projected to 3D	Body length, body height, hip height, chest depth	Average relative errors were 2.8%, 6.7%, 4.1%, and 4.4%, respectively
(Hou et al., 2025)	Angus, Simmental	Channel type	5 × IFM O3D303 LiDAR	Point cloud segmentation	Body height, body length, chest girth, abdominal circumference, hip height	Average relative errors were 4.96%, 5.47%, 6.04%, 5.68%, 5.49%, respectively
(Zhou et al., 2025)	Huaxi	Arch type	5 × Kinect DK	Point cloud segmentation + Adaptive cutting plane recognition	Withers height, body width, chest circumference, abdominal circumference	MAPE were 2.07%, 3.56%, 2.24%, 1.42%, respectively

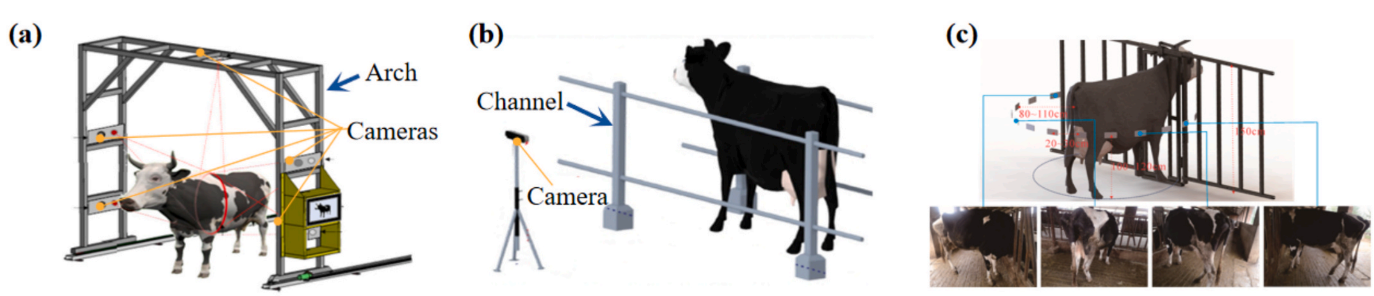


Fig. 5. Schematic diagram of data collection approaches. (a)-(c) respectively represent the collection scenarios based on arch type (Le Cozler et al., 2019a), channel type (Deng et al., 2025) and mobile type (Yang et al., 2023).

dimensions alone. In addition, to account for tissue density differences, some studies have also integrated ultrasonic parameters, such as Eye Muscle Area (EMA) and backfat depth (Song et al., 2018; Xavier et al., 2022). Collectively, these comprehensive and multi-dimensional features offer a more objective and precise description of cattle phenotypes, laying a robust foundation for the subsequent high-precision body weight estimation.

In the second stage, the extracted intermediate features were utilized as input variables for body weight prediction through various regression approaches. In these, linear regression remains a widely adopted approach due to its interpretability. For instance, Sakir et al. (2011) applied Multiple Linear Regression (MLR) to model WH, HH, BL, and HW, achieving a correlation coefficient of 0.9787. Similarly, Song et al. (2018) integrated HH, HW, and Rump Length (RL) with biological

Table 3
Representative studies on cattle body weight estimation.

Research	2D/3D Sensor	Breeds	Feature extraction method	Intermediate parameter	Regression approach	Performance
(Sakir et al., 2011)	4 × 2D cameras (Canon EOS400D)	Holstein cows	IA software (Delphi)	Wither height, hip height, body length, hip width	MLR	R^2 = 0.958;
(Song et al., 2018)	1 × 3D camera (Kinect)	Holstein cows	Manual point cloud analysis	Hip height, hip width, rump length, days in milk, parity, age	MLR	MAPE = 5.2%
(Nir et al., 2018)	1 × 3D camera (Kinect v2)	Holstein cows	Ellipse fitting	Ellipse radii, area, animal age	Quantile regression	R^2 = 0.95; RMSE = 22.57
(Miller et al., 2019)	1 × 3D camera (Basler, ToF)	Steer and heifer beef cattle	Manual analysis of 3D images	Eighteen body measurements, 20 ratios, 11 areas, 11 volumes (60 predictors in total)	ANN	R^2 = 0.7; RMSE = 42
(Le Cozler et al., 2019b)	5 × 3D cameras (Morpho3D, laser)	Holstein cows	Custom algorithm based on morphology	Volume, area, heart girth, chest depth, wither height, hip width, backside width, ischial width	MLR	R^2 = 0.93; RMSE = 18.2
(Cominotte et al., 2020)	1 × 3D camera (Kinect)	Nellore steers	Custom algorithm based on morphology	Dorsal area, body volume, body length, 6 widths, 6 heights	MLR + LASSO + PLS	R^2 = 0.79 ~ 0.93; RMSE = 7.7 ~ 11.4
(Weber et al., 2020) Weber et al. (2020)	1 × 2D camera (MIDI brand)	Nellore steers	Active contour model and Convex hull	Dorsal contour perimeter, dorsal area, number of convex hull defects, Distances between points	Bagging	MAE = 13.44; RMSE = 15.88
(Dohmen et al., 2021)	2 × 2D camera	Holstein cows	Mask-RCNN	N/A	FC layer	R^2 = 0.91; RMSE = 27
(Xavier et al., 2022)	5 × 3D cameras (Morpho3D, laser)	Holstein cows	Metruxα software	Hip width, heart girth, chest depth, withers height, diagonal length, partial volume, partial surface area, dry matter intake, body condition score, gut fill	Mixed model	R^2 = 0.92; RMSE = 22.1
(Hou et al., 2023)	1 × 3D camera (IFM O3D303)	Beef cattle	PointNet++	Body length, chest girth	Johnson's method (Wangchuk et al., 2018)	RMSE = 10.2
(Bai et al., 2025)	Mobile phone	Horqin cattle	MobilePoseNet	Body length, withers height, heart girth, and hip length	ANN	R^2 = 0.897; RMSE = 13.101
(Peng et al., 2024)	1 × 2D camera (Hikvision brand)	Bos grunniens	YOLOv8 + Contour edge detection	Lengths and areas of different body parts	MLR	R^2 = 0.96; RMSE = 2.43
(Wang et al., 2025a)	1 × 3D camera (custom stereo camera)	Bos grunniens	YOLOv8-Pose	Body length, body oblique length, body height	GPR	R^2 = 0.72; RMSE = 31.0; MAPE = 0.12
(Zhang et al., 2025a)	2 × 2D camera	Beef cattle	Improved ResNeXt	N/A	FC layer	R^2 = 0.934; RMSE = 13.118

Note: "R^2" = Coefficient of Determination; "RMSE" = Root Mean Squared Error; "MAPE" = Mean Absolute Percentage Error.

factors (age, parity) into an MLR model, reducing the Mean Absolute Percentage Error (MAPE) to 5.2%. Conversely, to better capture complex non-linear relationships between morphometric traits and body weight, machine learning algorithms have gained prominence. Bai et al. (2025) employed BL, HG, WH, and Hip Length (HL) as inputs to a customized deep regression network, attaining an accuracy rate above 97% in Horqin cattle. Wang et al. (2025a) utilized Gaussian Process Regression (GPR) to model morphometric traits in yak heifers, demonstrating high accuracy and strong adaptability under real-world farming conditions.

Adopting a different paradigm, recent studies have explored end-to-end approaches to predict cattle body weight directly from raw images or point clouds. By bypassing the intermediate parameters extraction, these methods effectively mitigate the cumulative information loss inherent in multi-step processing pipelines. For instance, Dohmen et al. (2021) combined Mask-RCNN-based segmentation with a CNN regression model to estimate heifer body weight directly from top-view images, achieving a coefficient of determination (R^2) of 0.96 and a Root Mean Square Error (RMSE) of approximately 20 kg. Zhang et al. (2025a) developed a dual-input deep neural network for non-contact carcass weight estimation, integrating dorsal and abdominal features extracted from top- and side-view images. The model achieved an RMSE of 17.713 kg on the test set. Despite their high accuracy, these approaches face challenges in maintaining robustness under variations in camera parameters, viewing angles, and acquisition conditions, highlighting the need for improved data augmentation and training strategies to enhance model generalization.

Synthesizing the above discussion and Table 3, current methodologies generally fall into two paradigms: two-stage frameworks and end-to-end learning methods. The former focuses on exploring comprehensive intermediate features to objectively describe cattle conformation, while employing robust regression models to ensure predictive reliability. This approach offers high interpretability but relies heavily on feature quality. Conversely, the latter streamlines the pipeline by mapping raw data directly to weight, effectively reducing cumulative errors. However, its inherent lack of interpretability and high data dependency remain critical hurdles for broad adoption. Crucially, it should be emphasized that many current estimation approaches do not explicitly account for individual attributes—such as age, parity, feed intake, breed, sex, and pregnancy status—during model development. This limitation poses a significant challenge for PLF, which relies on long-term monitoring and precise management to accommodate individual variability.

3.3. Body condition scoring

Body Condition Score (BCS) serves as a key indicator of dairy cows' energy reserves. It reflects fat deposition and nutritional status independently of body weight or body size and correlates closely with milk production, reproductive performance, and health (Wildman et al., 1982; Swartz et al., 2025). Unlike body weight, which may fluctuate relatively rapidly due to changes in feed intake, hydration status, or physiological conditions, BCS changes more gradually because it reflects cumulative fat deposition and mobilization. Therefore, BCS functions primarily as a lagging indicator of long-term energy balance rather than short-term physiological variation. Conventional systems classify cows on a 1–5 scale by evaluating fat coverage at key anatomical landmarks (e.g., tailhead, loin, ribs), as illustrated in Fig. 6. However, manual assessment is inherently subjective and labor-intensive, limiting the feasibility of high-frequency monitoring in large-scale operations (Ferguson et al., 2006; Bewley et al., 2008; Li et al., 2019). To address this, automated evaluation methods have emerged, principally categorized into feature engineering-based and deep learning-based approaches.

Feature engineering-based methods rely on expert knowledge to extract geometric descriptors from images or point clouds. Early attempts focused on manual landmark annotation, where researchers utilized angles and curves derived from manually labeled points (e.g., hook bone, tail depression) for BCS prediction (Ferguson et al., 2006; Bewley et al., 2008). Subsequent studies advanced towards automated geometric analysis. Halachmi et al. (2013) analyzed body surface curvature and identified tail depressions and hook bone prominence as key predictors, achieving a correlation of 0.94 with manual scores. Similarly, Spoliansky et al. (2016) extracted 14 morphological features from 3D point clouds and applied regression models, attaining a Mean Absolute Error (MAE) of 0.26 and R^2 of 0.75 in BCS prediction. Expanding on single-view limitations, Song et al. (2019) integrated multi-view features from eight body regions using k-nearest neighbor classification, achieving a sensitivity of 0.72. While effective in controlled environments, these approaches face significant scalability issues: feature design is complex and performance is highly sensitive to environmental factors such as lighting variations and animal posture.

Deep learning-based methods automatically learn features using neural networks, eliminating the need for manual feature design and improving prediction accuracy. Given the inherently volumetric nature of body condition, depth-based approaches have gained significant traction. Alvarez et al. (2018) fed depth images combined with Fourier and Canny edge maps into a convolutional neural network, achieving 94% accuracy within $\pm$ 0.5 BCS. Zhao et al. (2023c) converting 3D point clouds into convex hull distance maps for EfficientNet, reducing errors to $<$ 0.25 BCS for 91.2%. Moving towards direct 3D analysis, Shi et al. (2023) applied an attention-guided model based on PointNet++, achieving 0.80 accuracy within $\pm$ 0.25 BCS. Similarly, Zhang et al. (2023a) proposed the LShapeAnalyser method, which quantifies local differences through complete point cloud shape correspondence, enabling highly automated scoring. Beyond pure depth, multi-modal and dynamic approaches have also emerged. Sun et al. (2019) integrated RGB, depth, and phase congruency into an improved DenseNet, reaching 0.98 accuracy within $\pm$ 0.5 BCS. In the realm of real-time video processing, Li et al. (2025a) developed a YOLOv5-based system that extracts key regions from RGB video sequences using tail tracking, ensuring consistent scoring in dynamic environments.

Based on the above and Table 4, automated BCS methodologies have progressed from extracting handcrafted morphological descriptors to learning high-dimensional features via deep neural networks. In terms of performance, deep learning approaches consistently outperform feature engineering methods, achieving higher accuracy and robustness against environmental variations. However, a fundamental limitation persists in that most current systems treat BCS as a discrete classification task, whereas body condition is biologically a continuous and differentiable variable. Consequently, future research must pivot towards constructing large-scale, balanced datasets to support continuous regression models, thereby capturing the subtle, gradual changes in energy reserves essential for precise nutritional management.

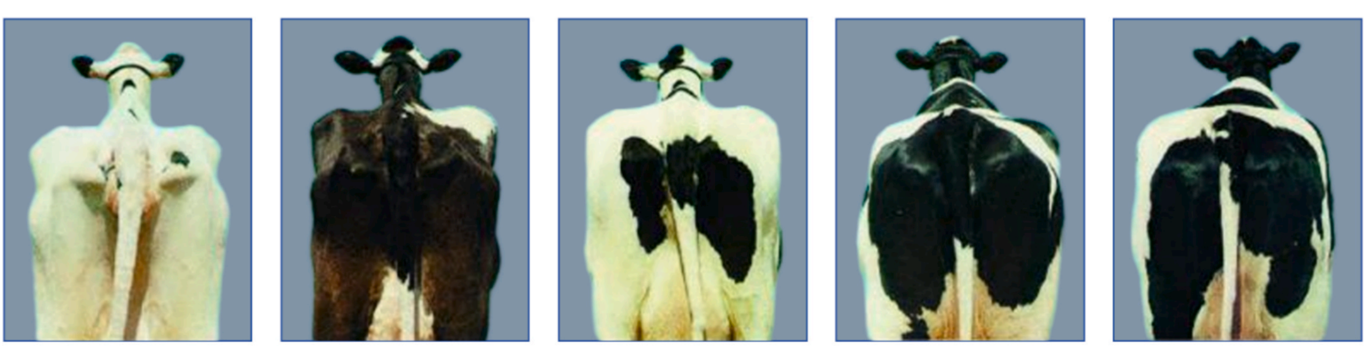
4. 3.Behavioral analysis

4.1. Basic behaviors

Basic behaviors of cattle, such as standing, lying, and walking, are fundamental indicators for characterizing individual health, welfare, and growth status (Qiao et al., 2022; Nasir et al., 2025). Continuous monitoring enables early detection of movement disorders, changes in comfort, and disease onset, offering critical information for precision feeding and health management (Shu et al., 2023; Zheng and Qin, 2023). In large-scale farming environments, traditional manual observation relies on direct recording or video review, which is time-consuming, labor-intensive, and subject to observer bias. Consequently, automated recognition methods have become essential for smart farming. The Fig. 7 illustrates key methodological milestones in this domain.

Early research primarily focused on static appearance analysis. Studies utilized contours or motion trajectories from single images or short clips to differentiate simple states like standing and lying These approaches are easy to implement but show limited robustness under varying lighting and occlusion, and are challenging to apply in group settings (Porto et al., 2013; Porto et al., 2015). They primarily relied on frame-based analysis to recognize static postures from individual images. However, such approaches cannot capture the intensity of movement or the temporal patterns of actions, such as the lying-down and rising behaviors.

To capture dynamic behavioral patterns more effectively, some work has pivoted towards spatiotemporal modeling, integrating spatial feature extraction with temporal sequence learning. For instance, combining 3D CNNs with optical flow (Fuentes et al., 2020) or Long Short-Term Memory (LSTM) networks (Yin et al., 2020; Wu et al., 2021) allows models to reliably distinguish behaviors even in complex environments. Advancing towards fine-grained motion modeling, recent architectures have focused on detecting subtle behavioral variations. Hao et al. (2024) introduced a dual-branch spatiotemporal network that processes spatial appearance and temporal dynamics in parallel, significantly improving generalization. Similarly, Geng et al. (2024)



(a) BCS=1 (b) BCS=2 (c) BCS=3 (d) BCS=4 (e) BCS=5

Fig. 6. Brief visualization of BCS estimation (Li et al., 2019). BCS = 1 representing extreme thinness and BCS = 5 indicating excessive condition.

Table 4
Representative studies on cattle body condition scoring.

Category	Research	Data type	Viewpoint	Algorithm	Key features	Cattle No.	Dataset Size	Performance
Feature engineering-based	(Ferguson et al., 2006)	Grayscale	Rear	Manual assessment	Tail head area	285	N/S	Corr: 0.76–0.90
	(Bewley et al., 2008)	Grayscale	Top	Regression	Hook angles	N/S	2,571	Acc $_{(\pm 0.25)}$: 92.8%
	(Halachmi et al., 2013)	Thermal	Top	Regression	Surface curvature	186	N/S	Corr: 0.94
	(Spoliansky et al., 2016)	Depth	Top	Regression	14 morphological features	101	14,474	MAE: 0.26; R^2: 0.75
	(Song et al., 2019)	Depth	Multi-view	KNN	8 body region features	44	N/S	Sensitivity: 0.72
Deep learning-based	(Alvarez et al., 2018)	Depth	Top	CNN	Fourier and Canny maps	N/S	1.661	Acc $_{(\pm 0.5)}$: 94%
	(Sun et al., 2019)	RGB-D	Top	Improved DenseNet	RGB, Depth, and Phase congruency	686	3,430	Acc $_{(\pm 0.5)}$: 98%
	(Zhao et al., 2023c)	Point cloud	Top	Improved EfficientNet	Convex hull distance map	77	5119	Acc $_{(\pm 0.5)}$: 97.60% Acc $_{(\pm 0.25)}$: 91.2%
	(Shi et al., 2023)	Point cloud	Top	Improved PointNet++	Point set features	512	3,660	Acc $_{(\pm 0.5)}$: 96% Acc $_{(\pm 0.25)}$: 80% Acc $_{(\pm 0.0)}$: 49%
	(Li et al., 2025a)	RGB	Rear	Improved YOLOv5	Tail regions	N/S	1611	mAP: 91.8%
	(Zhang et al., 2023a)	Depth	Multi-view	LShapeAnalyser	Multiple body parts	198	N/S	Acc $_{(\pm 0.5)}$: 100% Acc $_{(\pm 0.0)}$: 62.48%

Note: "MAE" = Mean Absolute Error; "Corr."= Correlation.

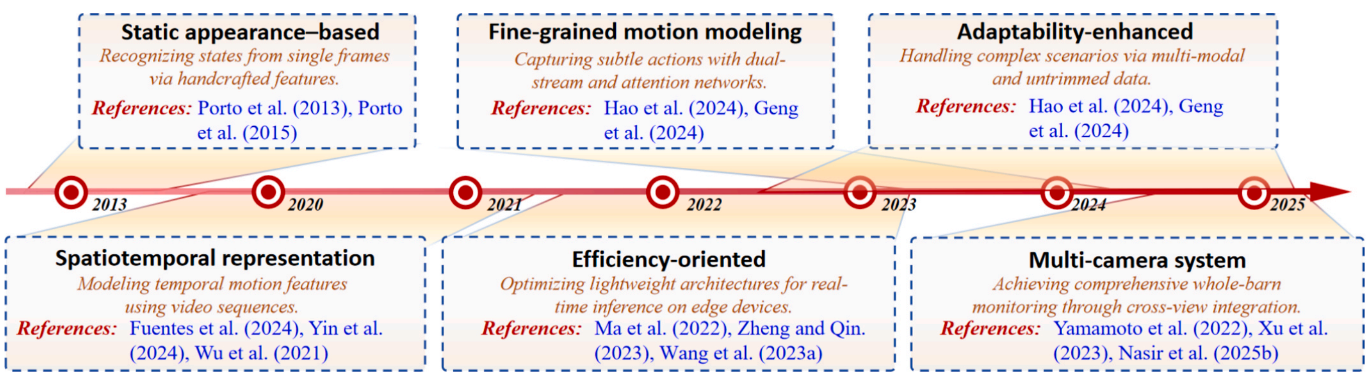


Fig. 7. Timeline of basic behaviors recognition.

proposed a hybrid framework where a global stream captures overall dynamics via Transformers, while a fine-grained motion stream utilizes focus convolution on frame differences to detect minute movements, thereby enhancing sensitivity to subtle actions.

Beyond accuracy, ensuring algorithmic efficiency and adaptability is critical for application. To meet efficiency requirements, lightweight architectures have been explored. Ma et al. (2022) and Wang et al. (2023a) introduced lightweight 3D convolutional architectures that significantly reduce computational overhead without compromising performance. Zheng and Qin (2023) achieved efficient dynamic monitoring by integrating a pruned YOLO network with multi-object tracking. To improve adaptability, some methods leveraged multi-modal information. Hua et al. (2023) modeled skeletal features to avoid direct dependence on appearance textures. Zhang et al. (2025b) fused video data with inertial sensor information, improving system stability and continuity in complex motion environments. Additionally, for long-duration video analysis, Han et al. (2025b) applied temporal localization in untrimmed natural scene videos, enabling precise annotation of continuous behavior segments and reducing biases and inefficiencies from manual segmentation.

Recently, multi-camera systems have been explored to enhance cattle behavior monitoring, addressing the limitations of single-camera setups such as restricted field of view, frequent occlusion, and uneven spatial resolution (Vu et al., 2024; Xu et al., 2025a). Yamamoto et al. (2025) introduced a location-based multi-camera tracking approach that enables continuous monitoring of all cattle within a barn and maintains reliable individual identification even under dense or dynamic herd conditions. Similarly, Xu et al. (2025a) developed the Multi-Camera Multi-Cow Tracking (MCMCT) framework, which integrates geometric mapping, posture-aware temporal smoothing, and trajectory association to achieve accurate cross-camera tracking of multiple individuals. Furthermore, Nasir et al. (2025) combined multi-camera fusion with Bird's-Eye-View (BEV) mapping, leveraging deep learning models to detect behaviors from multi-view videos and projecting the results onto a unified top-down view for precise localization and real-time recognition of individual cows. Collectively, these studies demonstrate the feasibility of achieving continuous, comprehensive, and high-precision monitoring of group-level cattle behaviors across large barn areas, forming a methodological basis for subsequent research in complex behavior analysis, health assessment, and intelligent farm management.

Building on the above analysis and Table 5, basic behavior recognition has evolved from analyzing static frames to modeling continuous spatiotemporal dynamics to capture subtle motion patterns, and from

Table 5
Representative studies on cattle basic behavior recognition.

Primary objective	Research	Input data	Key algorithm	Behaviors recognized	Performance
Static appearance-based	(Porto et al., 2013)	Top-view image	Viola-Jones	Lying	Sensitivity: 92%
	(Porto et al., 2015)	Top-view image	Viola-Jones	Standing, feeding	Sensitivity: 87–92%
Spatiotemporal modeling	(Fuentes et al., 2020)	Video + Optical flow	YOLOv3 + 3D-CNN	Walking, standing, eating, resting, et. al. (15 types)	mAP: 75.3–93.1%
	(Yin et al., 2020)	Video	EfficientNet + LSTM	Walking, drinking, lying, standing, feeding	Acc: 97.87%
	(Wu et al., 2021)	Video	VGG16 + Bi-LSTM	Walking, drinking, lying, standing, ruminating	Acc: 97.59%
	(Hao et al., 2024)	Video + Optical flow	Dual-stream network	Walking, drinking, lying, standing, eating, looking back	Acc: 96.53%
	(Geng et al., 2024)	Video	Dual-stream network	Drinking, grazing, other	Acc: 79.4%
Efficiency optimization	(Ma et al., 2022)	Video	Rexnet 3D CNN	Walking, lying, standing	Acc: 91.02%
	(Wang et al., 2023a)	Video	Efficient 3D CNN	Walking, drinking, lying, standing, feeding	Acc: 98.17%
	(Zheng and Qin, 2023)	Video	PrunedYOLO + C-BIoU Tracker	Walking, drinking, lying, standing	mAP:88.4%
Adaptability enhancement	(Hua et al., 2023)	Skeleton	YOLOX-Pose + PoseC3D	Walking, drinking, lying	Acc: 92.6%
	(Zhang et al., 2025b)	Video + Sensor (IMU)	Modality mapping net	Walking, drinking, lying, standing, feeding	Acc: 97.87%
	(Han et al., 2025b)	Untrimmed Video	ASGP-IDet	Mounting, running, fighting	mAP: 92.13%
Multi-camera systems	(Yamamoto et al., 2025)	Multi-view Video	BEV mapping	Barn-wide tracking	MOTA: 86.5%; IDF1: 81.4%
	(Xu et al., 2025a)	Multi-view Video	Spectral clustering	Cross-camera tracking	MOTA: 97.00%IDF1: 82.23%;
	(Nasir et al., 2025)	Multi-view Video	BEV mapping	Walking, standing, eating, resting, et. al. (15 types)	mAP: 85.6%

single-view monitoring to comprehensive multi-camera surveillance to overcome occlusion and expand monitoring coverage. Technologically, research focus has shifted towards deployment feasibility, with a strong emphasis on model efficiency and handling untrimmed video streams. Future research can delve into ensuring robustness in long-duration monitoring against environmental variations through multi-modal fusion, further optimizing lightweight architectures for edge deployment, and rigorously verifying the feasibility of multi-camera systems in commercial settings.

4.2. Reproductive behavior

Estrus and calving are critical behaviors in cattle production systems, as they directly affect reproductive efficiency, calving intervals, genetic improvement, and overall productivity (Senger, 1994; Cangar et al., 2008). Accurate and timely detection of these behaviors is essential for successful breeding, minimizing economic losses, and enhancing herd performance. Traditional reproductive management relies on manual observation or limited sensor tools such as pedometers, which are labor-intensive, subjective, and susceptible to missed or inaccurate detections, particularly in large-scale or grazing operations. Automated and intelligent monitoring of reproductive behaviors has therefore emerged as a key focus in PLF.

4.2.1. Estrus detection

Estrus monitoring is a key component of reproductive management in cows. In Holstein dairy cows, the estrous cycle is approximately 21 days, and each estrus lasts only 4 to 26 h, providing a very narrow optimal insemination window (Silper et al., 2015). Delayed artificial insemination can reduce conception rates and extend calving intervals, causing substantial economic losses (Roelofs et al., 2010). During estrus, cows display observable behaviors such as increased mounting activity, being mounted by other cows, and changes in movement patterns. These behaviors offer potential cues for estrus detection. Fig. 8 illustrated the chronological evolution of all estrus detection approaches referenced in this subsection.

Mounting behavior, the primary visual sign of estrus, has been the focus of early and current research. Technologically, approaches have advanced from simple motion analysis to deep learning-based tracking. Early work by Tsai and Huang (2014) utilized high-intensity motion regions and foreground segmentation to identify mounting events. With the advent of deep learning, detection performance has significantly improved. For instance, Wang et al. (2022a) integrated attention mechanisms into detection models, achieving a mAP of 94.3%. Considering that mounting behavior often occurs at night, Li et al. (2024a) proposed the IATEFF-YOLO model, which combines an illumination-adaptive transformer with efficient feature fusion to achieve real-time and high-precision mounting detection under low-light conditions. Furthermore, the focus has shifted from mere detection to continuous tracking. Concretely, Wang et al. (2025e) proposed the YOLO-TransT model, which extends mounting behavior detection by enabling precise tracking of the mounted cow. This improvement

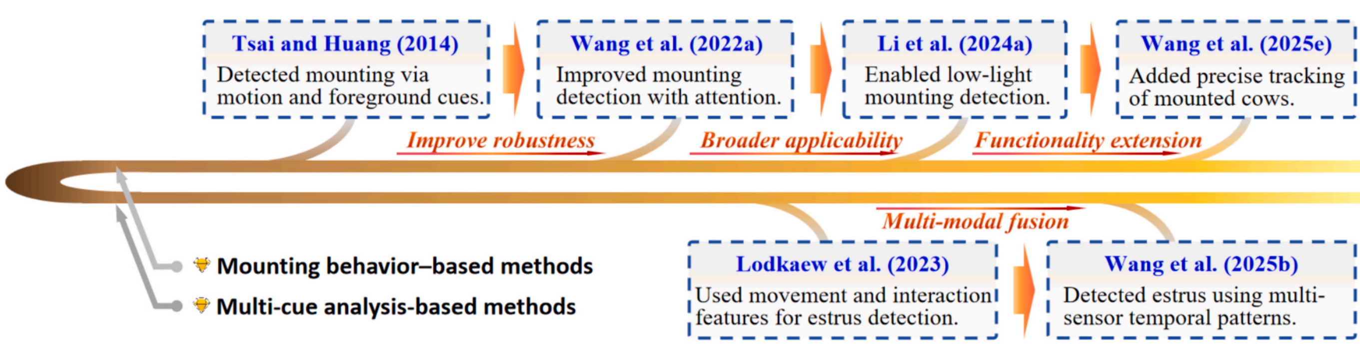


Fig. 8. Timeline of estrus detection methods.

substantially reduces the time and labor involved in locating estrus cows after mounting events.

However, relying exclusively on mounting behavior presents inherent limitations. As noted by Kerbrat and Disenhaus (2004) and Suzuki et al. (2024), some cows exhibit "silent estrus" (Shipka, 2000) with minimal mounting, while others may perform playful mounting when not in estrus. Such variations significantly constrain the reliability of single-cue models.

To mitigate these issues, recent studies have explored multi-cue analysis. Beyond the primary visual cue of mounting, researchers have investigated secondary behavioral features and overall movement patterns to achieve more comprehensive detection. For instance, Lodkaew et al. (2023) expanded the detection framework by integrating individual movement dynamics (e.g., velocity, acceleration) with inter-cow interactions (e.g., sniffing, resting), thereby enhancing the comprehensiveness and accuracy of estrus detection. Wang et al. (2025b) employed data fusion and signal analysis to identify estrus-specific patterns such as frequent circling and restless standing. By extracting time-series features via Fast Fourier Transform (FFT) and Principal Component Analysis (PCA), this method facilitates continuous and dynamic assessment, effectively capturing subtle behavioral deviations indicative of estrus.

Synthesizing the above discussion and the insights from Table 6, automated estrus detection has evolved from monitoring single mounting events to analyzing holistic behavioral patterns. Technological advancements have significantly enhanced detection robustness, effectively mitigating challenges associated with low-light conditions and complex scenes. However, given the inherent biological limitations of relying on a single sign, future research should further explore multi-cue integration. Moreover, developing adaptive models that explicitly account for individual attributes, including age, parity, breed, and environmental context, will be a critical anchor for achieving precise and personalized reproductive management.

4.2.2. Calving prediction

Calving represents a critical juncture in the reproductive cycle, where timely intervention is paramount to reducing dystocia rates and calf mortality. Accurate prediction of calving onset relies on identifying specific behavioral precursors (Cangar et al., 2008; Yang et al., 2024b; Mg et al., 2026). As illustrated in Fig. 9, contemporary research typically follows a systematic framework: behavioral indicators are first extracted from video or sensor data, and subsequently analyzed using statistical modeling or machine learning approaches to estimate calving time and assess the necessity for human assistance.

Several studies have sought to identify behavioral indicators that reliably signal the onset of calving. For instance, Sumi et al. (2021) monitored 25 pregnant cows in calving pens and manually annotated their behavioral sequences from video data. By integrating these sequences with a Hidden Markov Model (HMM), they demonstrated that frequent postural transitions serve as reliable predictors of imminent calving. Along the same line, Maw et al. (2021) proposed an absorbing Markov chain model to characterize behavioral state transitions and estimate the expected time of calving, further supporting the effectiveness of probabilistic behavior modeling for calving prediction. Similarly, Jensen (2012) observed that, within six hours prior to parturition, cows exhibited a marked increase in lying bouts and activity levels, along with characteristic behaviors such as looking back toward the abdomen. Moreover, Miedema et al. (2011) found that tail raising occurred earlier in heifers than in multiparous cows, highlighting the influence of age on calving behavior.

With the progress of tracking and posture analysis technologies, fully automated calving prediction systems have emerged. Hyodo et al. (2020) introduced a multi-feature detection framework that leveraged ResNet-50 and YOLOv3 to extract postural, motion, and orientation features of dairy cows. These features were accumulated into time-series statistics updated every seven minutes, where postural and rotational cues were processed by a fully connected network, and motion-related features were analyzed through a one-dimensional convolutional network, achieving a prediction accuracy of 86%. Building on similar concepts, Khin et al. (2024) utilized Detectron2-based Mask R-CNN and YOLOv8 to detect key behavioral cues such as "tail raising" and "stretch-sitting," enabling the differentiation of normal versus abnormal calving. More recently, Mg et al. (2025) designed a specialized cattle tracking algorithm that computed Cumulative Euclidean Distance (CD), Cumulative Magnitude of Acceleration (CA), and Cumulative Moving Average of Triangle Area (CMA) to identify individuals and estimate calving time, yielding an impressive 99% accuracy in distinguishing abnormal from normal cows within 12 h.

Synthesizing these developments, the automation of behavioral monitoring for calving prediction has received growing emphasis, offering a promising pathway to further reduce dystocia rates caused by delayed intervention. Nevertheless, current approaches remain highly dependent on a limited set of key behavioral cues, exhibiting constrained adaptability to individual variability and environmental noise. Future work should therefore aim to enhance the robustness and scalability of predictive models to ensure reliable performance under diverse farm conditions.

5. Vital signs monitoring

5.1. Technologies for body temperature

Body temperature represents the balance between heat production and dissipation, serving as a critical indicator of metabolic activity and overall health in cattle (Cai et al., 2023; Köhler et al., 2025). It generally refers to the average temperature of the body's internal core. While rectal and vaginal temperatures are regarded as clinical gold standards due to their stability, these approaches are labor-intensive, stress-inducing, and lack automation, making them unsuitable for precision livestock management. To address this limitation, several alternative methods have been investigated. Semi-invasive or implantable sensors,

Table 6
Representative studies on automated cattle estrus detection.

Category	Research	Features used	Key focus	Method	Performance
Mounting behavior detection	(Tsai and Huang, 2014)	Motion intensity	Event detection	Foreground segmentation	TPR: 100%FPR: 0.33%
	(Wang et al., 2022a)	Visual appearance	Dense scene robustness	Improved YOLO	AP_{estrus}: 93.90% $AP_{mounting}$:95.70%F1: 93.74%
	(Li et al., 2024a)	Visual appearance	Illumination-adaptive	Improved YOLO	mAP: 99.3%
	(Wang et al., 2025e)	Visual appearance	Continuous tracking	YOLO + TransT	AP_{estrus}: 92.60% F1: 92.00%Tracking success rate: 70.3%
Multi-cue analysis	(Lodkaew et al., 2023)	Distance, velocity, acceleration, coordinate, and nearest neighbor features	Multi-cue integration	LightGBM	F1: 91%
	(Wang et al., 2025b)	Position, velocity, and direction features	Time-series patterns	YOLO + DeepSORT + FFT + PCA	Acc: 89%

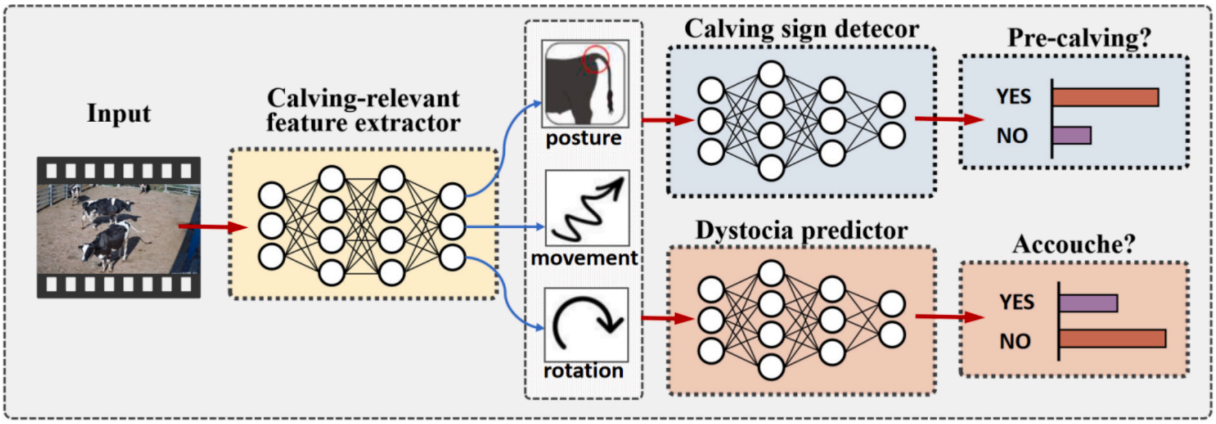


Fig. 9. Generic technical framework for calving time prediction.

including ear-tag thermometers and rumen temperature boluses, allow continuous monitoring but require individual installation, increasing both cost and animal burden (Zhang et al., 2021; Murugeswari et al., 2022; Chung et al., 2023). Hence, the development of non-contact, automated, and high-frequency temperature monitoring techniques is urgently needed.

Infrared Thermography (IRT) provides a promising non-contact solution (McManus et al., 2016; Pan et al., 2025). The technique measures mid- to long-wave infrared radiation emitted from the animal's surface to estimate body surface temperature indirectly. It eliminates stress responses associated with contact-based thermometry and enables continuous monitoring across multiple anatomical regions. In addition, IRT systems can be easily integrated into barn corridors, feeding zones, or milking stations, supporting real-time and automated temperature assessment.

Table 7 summarizes the IRT data acquisition configurations commonly applied in recent cattle temperature monitoring studies, focusing on the Region of Interest (ROI), camera setup, and emissivity. Typical ROIs include the udder, ears, hooves, and eyes, selected according to the analytical objective. For instance, eye temperature is frequently used to evaluate stress or general health (Shu et al., 2024b), while udder and mammary temperatures are applied in mastitis detection (Gayathri et al., 2024; Chu et al., 2025). In practical applications, automated ROI identification is increasingly achieved through computer vision techniques such as image segmentation or object detection (Shu et al., 2024b). To minimize measurement variability, most studies standardize emissivity at 0.98, which is considered the standard reference value in dairy thermography, reflecting the thermal properties of biological tissue (McManus et al., 2016; Velasco-Bolaños et al., 2021). Furthermore, acquisition distance is typically controlled within 1.0–2.0 m to balance ROI resolution and animal safety.

Table 7
Overview of the recent cattle body temperature monitoring work.

Research	Device	ROI	Image resolution (pixels)	Distance (m)	Emissivity
(Wang et al., 2024d)	FLIR A310	Eye and udder	320 × 240	1.80	–
(Gayathri et al., 2024)	Darvi DTL007	Eye and udder	384 × 288	1.00	0.98
(Shu et al., 2024b)	VarioCAM HR	Eye, muzzle, nostril, ear, and horn	640 × 480	1.00–1.50	0.98
(Little et al., 2025)	FLIR A310	Eye and udder	–	–	0.95
(Chu et al., 2025)	FLIR A310	Udder	320 × 240	1.80	0.98
(Köhler et al., 2025)	FLIR T1030sc	Tail tip	–	1.00	0.98
(Kim et al., 2025)	FLIR One Pro	Eye and muzzle	–	–	0.95

Despite standardization, the accuracy of IRT remains highly sensitive to external variables. Environmental conditions (Kastberger and Stachl, 2003), animal characteristics (McManus et al., 2016), and camera configuration (Church et al., 2014) influence the accuracy of IRT for body temperature measurement. Concretely, environmental factors such as wind, air temperature, and humidity can modify heat loss from the skin; Animal characteristics, including coat color, hair density, and surface dirt, affect convective heat dissipation; Camera-related factors, such as distance from the body and angle of incidence, also have a notable impact on temperature readings. To mitigate these influences, standardized calibration and appropriate data processing are required (Luo et al., 2025; Pan et al., 2025). For example, studies have shown that directly using raw IRT video data results in low correlation between eye temperature and rectal temperature, but it can be significantly improved by calculating rolling medians or quantiles (Cuthbertson et al., 2019). Even when the distance between the camera and the alley is controlled, walking cows can change the distance and incidence angle in images. These changes affect temperature readings of the eye, udder, and mammary regions. The peak-to-trough variation in eye temperature can reach 2.2 °C, and the temperature difference in the udder and mammary regions ranges from 0.6 to 2.0 °C. Such fluctuations can mask temperature changes associated with monitored conditions and significantly reduce the reliability of alert systems (Little et al., 2025). Therefore, temperature correction studies and the development of corresponding standards are essential to minimize measurement errors.

Synthesizing the discussion above and Table 7, IRT has cemented its role as the premier non-contact modality for temperature monitoring, offering effective alternatives to invasive sensors. However, the sensitivity of IRT to environmental factors and geometric variations remains a critical limitation. Consequently, future research should focus on developing robust environmental compensation algorithms and dynamic calibration models to bridge the gap between surface thermal patterns and reliable core temperature estimation.

5.2. Technologies for respiration rate

Respiration Rate (RR) is an important physiological indicator reflecting cattle health and environmental adaptability. Abnormal changes in RR indicate responses to stress or pathological conditions, including respiratory diseases, heat stress, or unsuitable housing (Zhang et al., 2024c). Non-contact monitoring has emerged as a key solution to replace manual counting. As summarized in Table 8, current approaches primarily leverage IRT, RGB Video, and FMCW Radar.

IRT is among the earliest methods used for monitoring RR. This technique estimates RR by capturing temperature fluctuations around the nostrils during the breathing cycle, as illustrated in Fig. 10. Early studies showed a strong correlation between RR measured by IRT and manual visual observations, with $R^2 \approx 0.93$, confirming the feasibility of non-contact respiration monitoring (Lowe et al., 2019).To enhance automation, recent frameworks integrate object detection or key-point tracking to localize nostrils, pushing detection accuracy above 96% even in low-resolution thermal videos (Kim and Hidaka, 2021; Zhao et al., 2023a; Chen et al., 2025a). However, while highly accurate, it remains limited by equipment cost and dependence on imaging distance in dynamic environments.

RGB Video-based methods focus on analyzing subtle body movements, such as lateral abdominal rise and fall during breathing. Initial efforts established the baseline for single animals. Wu et al. (2020b) combined segmentation models, Phase-Based Video Magnification (PBVM), and the Lucas-Kanade (LK) optical flow method to extract respiratory signals from standing cows, achieving nearly 98% accuracy. Subsequent studies scaled this approach to multi-cow monitoring in free-stall barns. By integrating object detection with advanced signal processing (e.g., FFT, filtering, optical flow), researchers have successfully balanced real-time performance with robustness in complex environments (Wu et al., 2023; Mantovani et al., 2024; Shu et al., 2024a; Wang et al., 2024c). A significant methodological shift is the move towards end-to-end learning. Wang et al. (2024a) further proposed an end-to-end Transformer architecture that predicts respiration rate directly from raw video, reducing errors associated with multi-step processing. Overall, RGB-based methods offer superior scalability and practical applicability, as they leverage standard surveillance infrastructure without requiring specialized sensors.

Frequency Modulated Continuous Wave (FMCW) radar has recently been introduced for cattle respiration monitoring (Tuan et al., 2022). The method captures subtle lateral abdominal movements using millimeter-wave radar to estimate respiration rate. Detection results show a high correlation with manual observations ($R^2 \approx 0.99$) and demonstrate long-term stability. Compared with infrared thermography and RGB video-based approaches, FMCW radar offers superior robustness against lighting conditions and occlusions. However, challenges remain in simultaneously monitoring multiple cows and managing equipment costs.

Table 8
Respiration rate monitoring methods.

Sensor data type	Research	Region of animal	Accuracy	R2	RMSE
Infrared video	(Lowe et al., 2019)	Nose	–	0.93	–
	(Kim and Hidaka, 2021)	Nose	–	0.91	–
	(Zhao et al., 2023a)	Nose	94.58%		–
	(Chen et al., 2025a)	Nose	96.30%	0.92	3.53
RGB video	(Wu et al., 2020b)	Abdomen	93.04%	–	–
	(Wu et al., 2023)	Abdomen	93.56%	–	3.74
	(Wang et al., 2024c)	Abdomen	92.00%	0.74	–
	(Shu et al., 2024a)	Abdomen	–		5.35
	(Mantovani et al., 2024)	Abdomen	–	0.73	8.3
	(Wang et al., 2024a)	Abdomen	–	0.74	3.52
	(Curti et al., 2025)	Abdomen	–	–	4.66
FMCW radar	(Tuan et al., 2022)	Abdomen	–	0.995	1.582

Synthesizing the preceding analysis, current RR monitoring methodologies exhibit distinct trade-offs: IRT offers high signal clarity but incurs high costs; RGB video provides scalable, low-cost deployment but remains vulnerable to illumination variations; and FMCW radar ensures environmental robustness but currently lacks multi-target capability. Consequently, future research must prioritize multi-modal fusion techniques. By integrating RGB with Radar or Thermal data, systems can combine scalability with robustness, ensuring reliable monitoring across diverse farm environments. Additionally, developing behavior-aware algorithms to filter motion artifacts will be critical for practical deployment in active herds.

5.3. Technologies for heart rate

Heart rate serves as an important indicator of stress response and energy metabolism in animals. In cases of stress or suboptimal health, the hypothalamus induces an elevated heart rate through neural and humoral regulation to maintain physiological balance. So, heart rate has been widely applied for evaluating environmental stress and predicting disease risk (Chen et al., 2022). Traditional monitoring relies mainly on implanted sensors or electrode patches with wireless data transmission. These methods provide high accuracy but may cause physical harm, require complex operation, and are challenging to implement in production settings. Electrocardiogram (ECG) is considered the clinical standard due to its reliability and precision, yet its application in large-scale herd management remains limited.

Non-contact heart rate monitoring is still in an exploratory stage. Remote photoplethysmography (rPPG) captures subtle skin color changes caused by cardiac pulsation using a camera to estimate heart rate (Wang et al., 2021). This approach is low-cost and contact-free but is strongly influenced by hair coverage. Another emerging method is Magnetocardiography (MCG), which relies on biomagnetic signals. Sutter et al. (2020) used a gradiometer system constructed from optical-pumped magnetometers to record heart rate in farm environments without direct contact. The results showed that MCG signals can be synchronized with ECG recordings and can successfully identify cardiac features, including P waves, QRS complexes, and T waves. These findings demonstrate the feasibility of MCG monitoring without magnetic shielding and indicate its potential as a non-contact, remote heart rate detection technique for livestock.

6. Diseases detection

6.1. Mastitis detection

Mastitis is one of the most prevalent diseases in dairy cows (Tommasoni et al., 2023). Statistics show that at least one-third of all dairy cows worldwide are affected by some form of mastitis (Tenhagen and Heuwieser, 2006; Dabele et al., 2021; Chu et al., 2023b). Based on pathological signs and milk secretion indicators, mastitis condition is generally classified into three categories: Healthy, Subclinical, and Clinical (Kemp et al., 2008; Dahl et al., 2018). Clinical mastitis presents with udder swelling, pain, and abnormal milk, while subclinical mastitis is often visually undetectable and is primarily indicated by elevated somatic cell count or changes in milk composition. Because of its asymptomatic nature, subclinical mastitis can easily go unnoticed, leading to production losses and chronic inflammation. Therefore, its early detection is of great importance.

The conventional methods for detecting subclinical mastitis on dairy farms typically rely on complex laboratory procedures, such as Somatic Cell Count (SCC), the California Mastitis Test (CMT), and enzymatic or microbiological analyses of milk (Kandeel et al., 2019; Stanek et al., 2024). In addition, Automatic Milking Systems (AMS) can enable

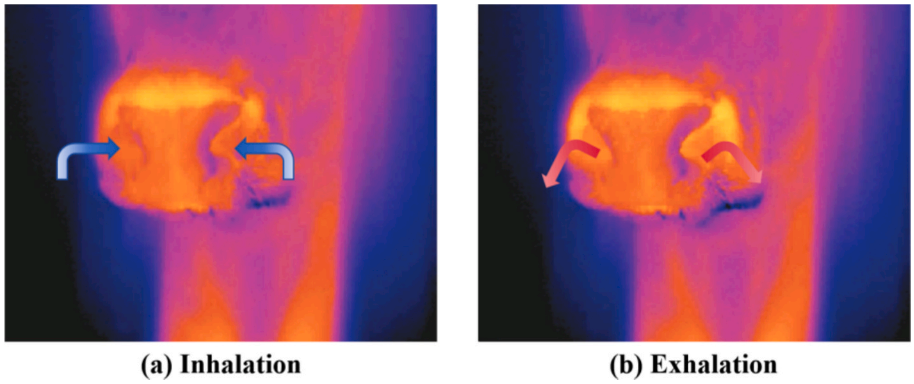


Fig. 10. Infrared images capturing nostril thermal changes (Stewart et al., 2019).

continuous screening and early warning during lactation by monitoring real-time indicators such as milk electrical conductivity, yield, and compositional changes (de Mol and Ouweltjes, 2001; Prus et al., 2025). However, their effectiveness is limited during the dry period or when milking frequency is low, which constrains the feasibility of whole-cycle mastitis monitoring. Therefore, developing non-contact, all-day mastitis detection methods is of practical importance.

IRT has emerged as a promising non-contact technique for the early detection of mastitis (Korelidou et al., 2024). Operating on the principle that inflammation-induced vasodilation leads to localized hyperthermia, IRT can directly capture thermal difference between healthy and infected tissue (as shown in Fig. 11). Previous studies have demonstrated that IRT effectively differentiates healthy, subclinical, and clinical cases, demonstrating strong correlations with somatic cell count (SCC) and clinical scores. These findings confirm the potential of IRT for mastitis monitoring (Metzner et al., 2015; Velasco-Bolaños et al., 2021; Khakimov et al., 2022).

Some studies focused on directly analyzing absolute thermal data from the udder surface. By leveraging automated ROI localization, Watz et al. (2019) achieved over 90% sensitivity and specificity in detecting *E. coli*-induced clinical mastitis via active shape modeling. Advancing beyond simple thresholds, deep learning approaches have been applied to extract complex thermal patterns. For instance, CNN-based frameworks have been developed to classify udder thermograms directly, achieving high accuracy by learning discriminative features from the absolute thermal distribution (Gayathri et al., 2024; Gayathri et al., 2025). Nevertheless, relying solely on absolute temperature makes these models vulnerable to environmental fluctuations and individual variability, limiting their robustness in uncontrolled settings.

To minimize the impact of ambient temperature fluctuations on diagnosis, several studies have introduced relative temperature difference features as an alternative to absolute temperature. Zhang et al. (2020) developed a deep learning-based EFMYOLOv3 model that automatically detects the eye and udder regions of dairy cows and calculates the eye–udder temperature difference for mastitis identification. To further mitigate environmental interference and occlusion effects, advanced segmentation models such as DeepLabV3 + and improved U-Net have been employed to extract eye and udder regions, enabling robust mastitis classification based on temperature gradients (Zhang et al., 2023b; Wang et al., 2024d). Additionally, Wang et al. (2022b) combined the bilateral udder surface temperature difference with the eye–udder temperature difference, effectively reducing environmental bias and enhancing diagnostic accuracy and sensitivity. Collectively, these studies highlight that relative temperature difference features offer greater robustness and reliability than absolute temperature measurements. However, single temperature features remain limited in their ability to detect subclinical mastitis at an early stage.

To address the above limitation, recent studies have integrated multimodal or multidimensional features to enhance both accuracy and robustness. Chu et al. (2023a) combined udder temperature with morphological characteristics. Temperature distribution and geometric keypoint features of the udder were extracted using YOLOv7 and CenterNet, respectively, and an SVM classifier was applied to differentiate mastitis types, achieving an accuracy exceeding 88%. Chu et al. (2025) introduced a multi-feature image-layer fusion approach, extracting temperature distribution, vascular structure, and udder size features simultaneously from thermal images. These features were jointly analyzed with a deep learning model, demonstrating improved identification of subclinical mastitis. This multimodal fusion strategy overcomes the limitations of single temperature features and shows strong potential for accurate mastitis monitoring in complex farming scenarios.

Synthesizing the above discussion and Table 9, automated mastitis diagnosis has progressed from simple temperature-threshold assessments to deep learning-driven multidimensional feature modeling. Technologically, the integration of relative temperature differentials and morphological features has significantly improved robustness

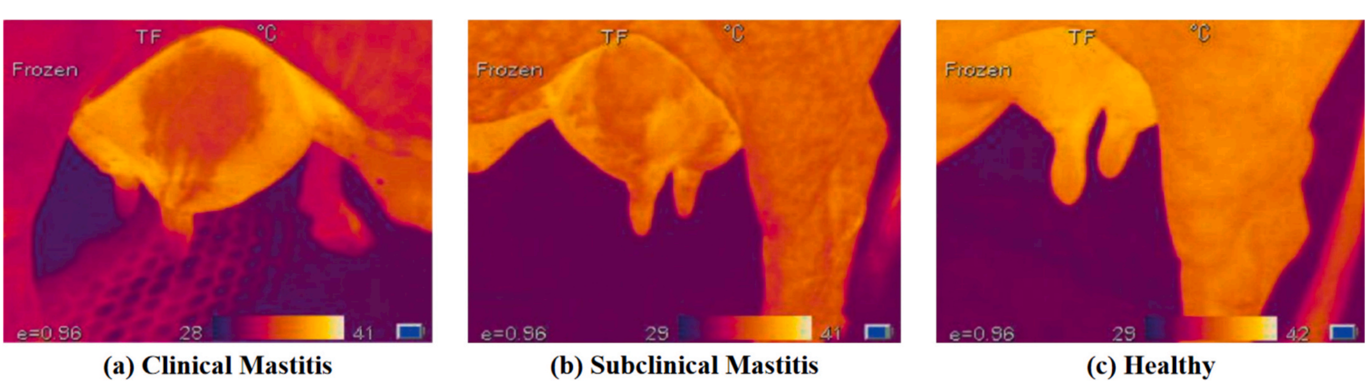


Fig. 11. Thermal infrared imaging of cattle udders with varying severities of mastitis (Gayathri et al., 2025).

Table 9
Representative studies on IRT-based mastitis detection.

Category	Research	ROI	Algorithm	Key features	Performance
Absolute temperature-based	(Watz et al., 2019)	Udder	Active shape model	Surface temperature	Sensitivity: 93.75%; Specificity: 94.96%
	(Gayathri et al., 2024)	Udder	CNN model	Udder skin surface temperature distribution	Acc: 94.30%
	(Gayathri et al., 2025)	Udder	CNN model	Udder skin surface temperature distribution	Acc: 71%
Relative temperature-based	(Zhang et al., 2020)	Eye and udder	Improved YOLO v3	Ocular surface temperature and udder skin surface temperature	Acc: 83.33%; Sensitivity: 92.31%; Specificity: 76.47%
	(Wang et al., 2024d)	Eye and udder	DeepLabV3 + Improved YOLO v5	Ocular surface temperature and udder skin surface temperature	Acc: 86%; Sensitivity: 79.41%; Specificity: 92.49%
	(Zhang et al., 2023b)	Eye and udder	Improved U-Net	Ocular surface temperature and udder skin surface temperature	Acc: 86.67%;Sensitivity: 82.35%
	(Wang et al., 2022b)	Eye and bilateral udder	Improved YOLO v5	Bilateral udder skin surface temperature and Ocular surface temperature	Acc: 87.62%; Sensitivity: 84.62%; Specificity: 87.62%
Multi-feature fusion-based	(Chu et al., 2023a)	Udder	YOLO v7 + CenterNet + SVM	Udder skin surface temperature distribution and udder size	Acc: 88.61% Sensitivity: 87.50%; Specificity: 94.03%
	(Chu et al., 2025)	Udder	DenseNet	Udder skin surface temperature distribution, vascular structure, and udder size	Acc: 91.88%

against environmental noise. Nevertheless, the robustness of these approaches under varying environmental conditions and across different animal populations remains limited. Future research should focus on feature integration, model generalization, and practical system deployment to enhance reliability and applicability.

6.2. Lameness detection

Lameness is one of the most prevalent and impactful health problems in herds, commonly resulting from hoof disorders, injuries, suboptimal housing, and nutritional imbalances. Global surveys report that lameness affects approximately 25% of cattle consistently (Robcis et al., 2023; Thomsen et al., 2023). The condition restricts normal movement, reduces feed intake and reproductive performance, and significantly lowers milk production and growth, leading to substantial economic losses and compromised animal welfare (Sprecher et al., 1997; Denis-Robichaud et al., 2020). Clinically, affected cows often display asymmetric gait, arched back, head bobbing, and abnormal contact of the hind hooves with the ground (Sheng et al., 2025). However, detecting these subtle manifestations, particularly in early or mild cases, remains challenging through visual observation. Consequently, the development of automated detection methods based on objective indicators is essential for enhancing early diagnosis and improving herd management. Fig. 12 outlines the technological trajectory of lameness detection, which has progressed from static indicators to dynamic sequence modeling and ultimately to comprehensive multi-dimensional fusion.

Early research primarily focused on analyzing single clinical indicators, targeting either leg movements or back posture (Song et al., 2008; Poursaberi et al., 2010; Wu et al., 2020a). Regarding leg movements, methods quantifying hoof trajectories have been widely explored. For instance, the “tracking-up” distance (parameter b in Fig. 13) has proven to be a robust indicator, achieving a 94.8% correlation with ground-truth hoof positions when quantified via video

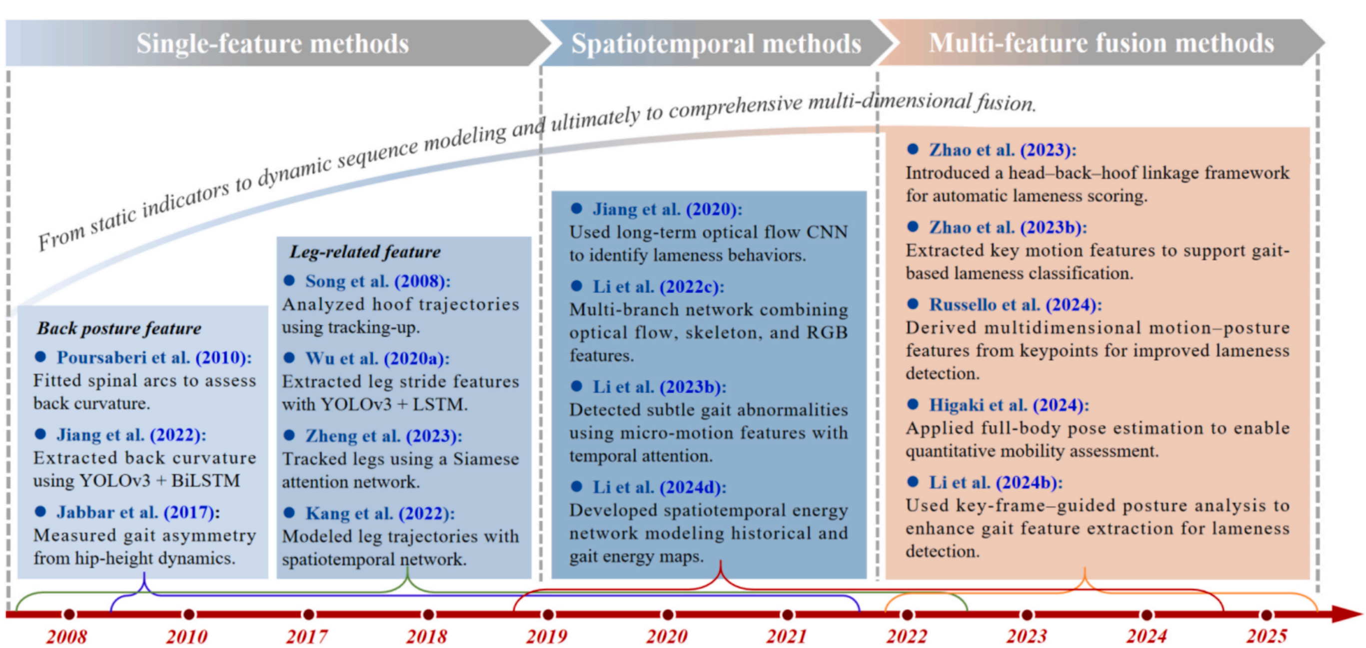


Fig. 12. Research timeline of non-contact cattle lameness detection technologies.

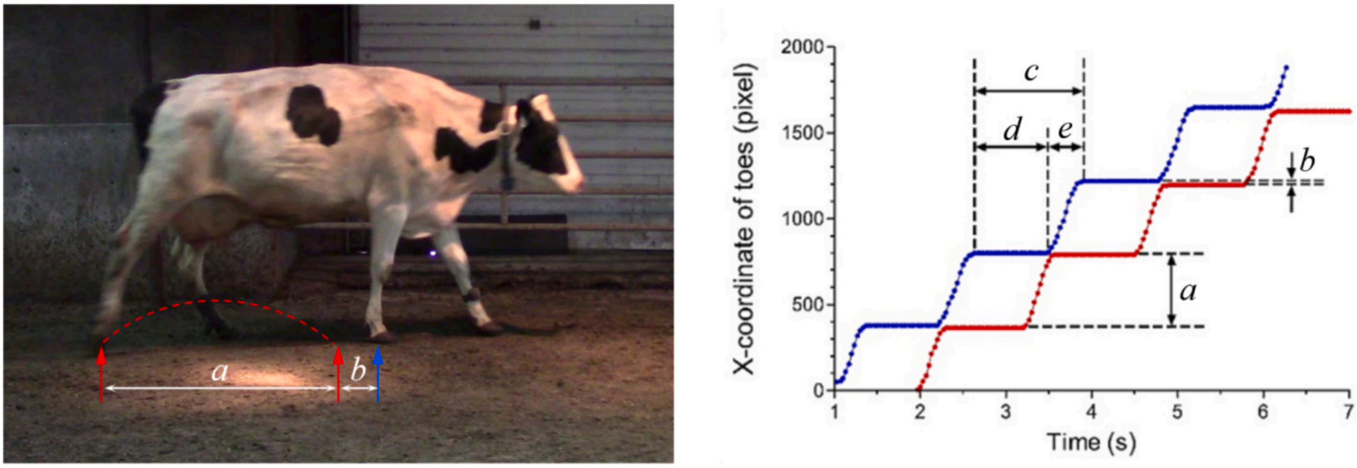


Fig. 13. Visual descriptions of the various parameters used to evaluate lameness (Higaki et al., 2024; Sheng et al., 2025). Parameters (a)–(e) represent stride length, tracking-up, stride duration, stance duration, and swing duration, respectively.

analysis (Song et al., 2008). Similarly, the fore- and hind-leg "stride length" (parameter *a* in Fig. 13) has shown exceptional discriminative power, enabling a lameness recognition accuracy of 98.57% when integrated into a YOLOv3-LSTM framework (Wu et al., 2020a). Further validating the efficacy of such leg-related features, Zheng et al. (2023) achieved 94.7% accuracy by classifying relative stride via Siamese attention networks, while Kang et al. (2022) attained over 98% precision by combining spatiotemporal background removal with DenseNet to analyze leg trajectories. Beyond leg movements, back posture has also been examined. Poursaberi et al. (2010) fitted spinal arcs to calculate back curvature and averaged multiple frames to assess lameness severity. Similarly, Jiang et al. (2022) combined YOLOv3 with BiLSTM models to extract temporal features of back curvature, achieving 96.61% accuracy. Back curvature can also be extracted from top-view depth imaging, where dorsal 3D features are used for lameness classification (Tun et al., 2024). Additionally, gait asymmetry has been validated as a critical indicator, with studies demonstrating that capturing 3D hip-height dynamics can effectively detect mild lameness (Jabbar et al., 2017). Overall, these single-feature methods are easy to interpret and conceptually straightforward, but their sensitivity to environmental conditions and individual differences limits both accuracy and generalizability.

To capture dynamic complexity more effectively, research shifted towards deep spatiotemporal modeling, aiming to fully exploit multi-dimensional video information (Jiang et al., 2020; Li et al., 2022c; Li et al., 2024d). Jiang et al. (2020) used a long-term optical flow convolutional network to identify typical lameness behaviors from short motion clips. Li et al. (2022c) proposed a multi-branch deep network that incorporated optical flow and skeleton features with RGB input, improving the recognition of motion and gait features and achieving 97.2% accuracy. Further innovations, such as micro-motion attention mechanisms (Li et al., 2023b) and spatiotemporal energy networks (Li et al., 2024d), have further enhanced the recognition of complex lameness patterns, pushing accuracy above 98%. However, though these methods reduce information loss compared with single-feature approaches, their generalizability and the interpretability of their predictions remain limited.

Most recently, the collaborative analysis of multidimensional motion and posture features for lameness detection has emerged as a dominant trend (Higaki et al., 2024; Li et al., 2024b). By adopting keypoint detection techniques, researchers can extract diverse motion-related features to facilitate the automated identification of early-stage lameness. For instance, Zhao et al. (2023b) extracted seven key features including head nodding and stride asymmetry, achieving robust classification using SVM. Similarly, Russello et al. (2024) utilized T-LEAP (Russello et al., 2022) to detect cattle skeletons and derive ten biomechanical features such as back posture and swing duration. These features were then processed by a Radial Basis Function SVM to enhance the discriminative power of lameness identification. Taking this further, Higaki et al. (2024) integrated 17 mobility variables into multiple linear regression models to predict mobility scores. These variables were derived from 25-keypoint pose estimation and encompassed spatial, temporal, and joint angle parameters. Crucially, these above studies further analyzed the relative importance of features in the decision-making process. Although the specific ranking varies, tracking-up (Song et al., 2008; Pluk et al., 2010), back angle (Poursaberi et al., 2010), head bobbing amplitude (Zhao et al., 2023b), and stride length (Flower et al., 2005; Blackie et al., 2013) are universally recognized as consensus important metrics for reliable lameness assessment.

Given that existing studies have not yet reached a consensus on the selection, definition, and nomenclature of motion-related features, a systematic summary and clear definitions of commonly used motion-related features are provided in Table 10, aiming to avoid inconsistencies in naming and definition across studies and to offer a unified and standardized reference for future research.

Synthesizing the discussion above and Table 11, automated lameness detection has transitioned from analyzing isolated clinical features to modeling holistic locomotion patterns. While end-to-end deep learning models have significantly improved accuracy, they often struggle with limited robustness against environmental noise and a lack of model interpretability. Consequently, recent methodologies have shifted towards pose-based multi-feature analysis, which leverages deep learning to robustly extract interpretable biomechanical indicators. Looking forward, future research must prioritize detecting subtle, pre-clinical anomalies and enhancing system resilience in complex, unconstrained environments.

6.3. Other disease detection

Beyond mastitis and lameness, non-contact detection of other cattle diseases has begun to receive attention (Hossein-Zadeh, 2025). Preliminary studies have explored hoof disorders, a major cause of lameness and economic loss, using integrated computer vision and infrared thermography systems to automatically detect and localize lesions under commercial farm conditions (Bumbálek et al., 2026). Similarly, cardiovascular diseases, which can severely affect heart and circulatory health, have been investigated through AI-based analysis of retinal images, where deep learning models such as ResNet101 showed promising diagnostic performance for early detection in cattle (Cihan et al., 2024). For neonatal calves, initial work has demonstrated non-contact

Table 10
Definition and standardization of features for gait analysis.

Feature	Alternative names	Symbol	Definition	
Distance-related features				
Stride length	Step size; Step length	f_{SL}	Horizontal distance traveled by a single hoof from one landing to its next landing.	
Tracking-up	Tracking distance; Overlap	f_{TU}	Horizontal distance between the landing point of a front hoof and the subsequent landing point of the ipsilateral hind hoof.	
Head bobbing amplitude	Head nod; Vertical head displacement	f_{Head}	Vertical distance traveled by the head between its highest and lowest positions during the whole stride.	
Back arch height	Back movement	f_{Back}	Maximum vertical distance of the back from a reference line connecting the withers and tailhead.	
Temporal-related features				
Stride duration	Step duration	t_{Str}	Time interval for a single hoof to complete a full gait cycle, from one landing to the next.	
Stance duration	Stance duration	t_{Sta}	Time interval during which a hoof remains in contact with the ground.	
Swing duration		t_{Swi}	Time interval during which a hoof is lifted and moves forward without contacting the ground.	
Stance phase	Supporting phase	ρ_{Sta}	Proportion of the gait cycle during which the specified hoof remains in contact with the ground.	
Swing phase		ρ_{Swi}	Proportion of the gait cycle during which the specified hoof is not in contact with the ground.	
Joint-related features				
Back angle		θ_{Back}	Ventral angle formed by the line connecting back-tailhead and back-withers.	
Neck tilt angle		θ_{Neck}	Angle of the neck relative to the horizontal axis or reference line at hoof landing.	
Joint contact angle	Joint strike angle	$\theta_{JC\_}$	Angle of a specified joint when the corresponding hoof begins ground contact and enters stance phase.	*Joint specification:* *Elbow*: between elbow-shoulder and elbow-carpus;
Joint release angle	Joint toe-off angle	$\theta_{JR\_}$	Angle of a specified joint when the corresponding hoof leaves the ground and enters swing phase.	*Stifle*: between stifle-tailhead and stifle-hock; *Carpus*: between carpus-elbow and carpus-front fetlock; *Hock*: between hock-stifle and hock-rear fetlock; *Front/rear fetlock*: between front/rear fetlock-hock and front/rear fetlock-toe.

Note: Superscripts L/R indicate Left or Right limb, F/H indicate Front or Hind limb. For example, f_{SL}^{RF} refers to the stride length of the right front hoof ; $\theta_{JC\_Elb}^{L}$ refers to the joint contact angle of the left front limb.

Table 11
Representative studies on automated cattle lameness detection.

Category	Research	Input Data	Algorithm	Key Features	Performance
Single-feature methods	(Song et al., 2008)	Side-view video	Background subtraction + Binary operations	tracking-up	Correlation coefficient: 94.8%
	(Poursaberi et al., 2010)	Side-view video	Background subtraction + Shape/circle fitting	Back curvature	Acc: 96.4%
	(Jabbar et al., 2017)	Overhead 3D depth video	Hilbert Transform + SVM	Gait asymmetry (hip height)	Acc: 96.4% Sensitivity: 100%; Specificity: 75%
	(Wu et al., 2020a)	Side-view video	YOLO v3 + LSTM	Relative step size	Acc: 98.57%
	(Jiang et al., 2022)	Side-view video	Improved YOLO v3 + BiLSTM	Back curvature	Acc: 96.61%
	(Kang et al., 2022)	Side-view video	YOLO v4 + DenseNet	Spatiotemporal gaitmap	Acc: 98.50% Sensitivity: 98.50%; Specificity: 99.25%
	(Zheng et al., 2023)	Side-view video	Siamese attention model + SVM	Relative step size	Acc: 94.73%
Deep spatiotemporal methods	(Jiang et al., 2020)	Side-view video + Optical flow	DenseNet + BiLSTM	Complex lameness patterns	Acc: 98.24%
	(Li et al., 2022c)	Side-view video + Optical flow + Skeleton data	Multi-branch network	Complex lameness patterns	Acc: 97.20%
	(Li et al., 2023b)	Side-view video	Focal convolution + Temporal attention Network	Complex lameness patterns	Acc: 98.89% Sensitivity: 98.89%; Specificity: 99.44%
	(Li et al., 2024d)	Side-view video	YOLO v8n + Dual MobileNetV2	History energy image, gait energy image	Acc: 96.22% Sensitivity: 96.35%; Specificity: 98.14%
Multi-feature integration methods	(Li et al., 2024b)	Side-view video	SOLOv2 + Hungarian algorithm + SVM	Neck and back contour, supporting phase, swing phase, step size, speed, overlap, gait symmetry	Acc: 98.65% Sensitivity: 100%; Specificity: 97.30%
	(Zhao et al., 2023b)	Side-view video	DeepLabCut + Logistic regression	Head-hoof linkage, back-hoof linkage, stride length, tracking up, landing speed, supporting phase, moving speed	Acc: 89.2%
	(Russello et al., 2024)	Side-view video	T-LEAP + SVM	Back posture, head bobbing, tracking-up, stride length, stance duration, swing duration	Acc: 80.07% Sensitivity: 76.78%; Specificity: 81.15%
	(Higaki et al., 2024)	Side-view video	25-keypoint pose estimation + Random forest	17 mobility variables (spatial, temporal, joint angles)	AUC: 0.86

monitoring for early disease detection, including diarrhea recognition via DenseDFFNet-based fecal segmentation (Pu et al., 2025) and abnormal respiratory behavior detection using an improved YOLOv5 with frame-difference analysis (Zeng et al., 2023). Collectively, these studies provide early evidence that automated, non-contact monitoring could be extended to a broader range of cattle diseases, supporting timely interventions and improved animal welfare.

7. Challenges and perspectives

In recent years, PLF has gained increasing attention in the cattle industry. Non-contact monitoring technologies have made notable progress across multiple fields. Most methods, however, remain at the laboratory or small-scale validation stage, and few have been applied at scale on commercial farms. This discrepancy is primarily due to limitations in data, technology, system integration, and evaluation methods. In this section, the current challenges and future directions were analyzed from four core dimensions.

7.1. Data silos

Challenge: High-quality data are the foundation for developing accurate automatic monitoring algorithms. However, publicly available datasets are very limited, and most research teams need to collect and annotate data by themselves (Bhujel et al., 2025). This results in insufficient samples, uneven class distribution, and large inter-team differences, which particularly affect the accuracy and generalization of deep learning models. Therefore, trained models are often influenced by environmental, lighting, seasonal, and individual variations, making it difficult to meet real-world deployment requirements (Yin et al., 2023). In addition, data generated daily on farms have not been fully utilized, forming data silos that further restrict the adoption of intelligent monitoring systems.

Perspective: Future efforts should promote data standardization and sharing to enable interoperability among research groups, farmers, and management enterprises. Some teams and platforms have already been advancing in this direction (Bhujel et al., 2025). For example, the Holistic Explainable Referential Datahub (HERD) big data platform (https://ai4as.cn/) can integrate multi-source information to improve data utilization efficiency (Zhou et al., 2026). Establishing unified data formats and labeling standards, combined with distributed storage, edge computing, and cloud platforms, could provide a foundation for model training, cross-scenario transfer learning, and real-time monitoring.

7.2. Technical limitations

Challenge: Despite the high accuracy demonstrated by non-contact monitoring technologies under controlled conditions, their practical deployment in farms remains constrained by limited precision, robustness, and real-time performance (Qiao et al., 2021; Wang et al., 2025d). On one hand, complex environmental factors such as illumination variation, occlusion, mud, and manure contamination often degrade sensor data quality and reduce detection reliability. On the other hand, most deep learning models contain large parameter volumes and rely heavily on high-performance hardware, making real-time inference difficult in resource-constrained farm environments. Furthermore, current models exhibit limited capability in recognizing abnormal events and insufficient generalization across different environments and cattle breeds.

Perspective: The future breakthroughs lie in multi-modal fusion, lightweight design, and intelligent models. From one perspective, integrating multi-source information such as infrared thermography, RGB imagery, radar, and depth data, can greatly enhance system robustness and accuracy under complex environmental conditions (Sapkota et al., 2025). From another perspective, lightweight strategies such as knowledge distillation, pruning, and quantization, should be explored to balance computational efficiency and predictive performance (Cheng et al., 2024; Bao et al., 2026). In addition, adopting autonomous learning and agent-based frameworks may endow monitoring systems with cross-scenario adaptability and continual learning capability, supporting long-term and all-weather operation in real farm environments (Xu et al., 2024b; Ma et al., 2025; Zhao et al., 2025).

7.3. Evaluation frameworks

Challenge: Existing evaluation methods focus primarily on technical indicators such as algorithm accuracy, detection rate, or inference speed. The preferences and needs of end users, including farm managers and veterinarians, are often overlooked. This misalignment between technical evaluation and practical adoption complicates accurate assessment of technology diffusion potential (Min et al., 2025). Furthermore, current evaluation systems insufficiently account for long-term effects on economic feasibility, animal welfare, and environmental sustainability, limiting the broader adoption of the technologies (Lovarelli et al., 2020).

Perspective: Future evaluation frameworks should incorporate multidimensional metrics, including user experience, economic benefits, animal welfare, environmental impact, and operational convenience, to ensure alignment between technology design and real-world application. Interdisciplinary collaboration is essential, drawing input from animal scientists, engineers, farm operators, and policymakers to refine evaluation systems (Wang et al., 2025d). Establishing such comprehensive metrics will improve the adoptability and long-term value of emerging technologies in precision livestock farming.

7.4. System integration

Challenge: Most existing studies focus on isolated functions, resulting in low system integration and the absence of a fully automated workflow from sensing and data acquisition to intelligent analysis. This limitation restricts large-scale deployment in commercial cattle farms and reduces stability and maintainability during prolonged operation.

Perspective: Future development should aim to transcend single-function solutions by constructing an integrated intelligent platform for comprehensive cattle monitoring. Such a platform should provide a fully automated closed-loop from data acquisition to analysis, ensuring real-time performance and scalability. In large-scale farms, continuous high-resolution video from hundreds to thousands of cows generates massive data streams that are difficult to transmit and process centrally. For long-term monitoring tasks, on-site real-time processing is essential to reduce latency and bandwidth usage, while aggregated or summarized information can be transmitted to cloud servers for storage, cross-farm integration, or higher-level decision-making. Therefore, designing appropriate hybrid local-cloud strategies is critical (Spana et al., 2026). Additionally, the integration of robotics and intelligent decision-making technologies may transform non-contact monitoring from passive observation into active intervention, ushering in a new era of smart management in precision livestock farming.

7.5. Application-specific considerations

To enable the practical adoption of non-contact monitoring technologies at commercial scale, it is essential to consider the specific workflows, deployment challenges, and future directions for each application.

For cattle identification, the workflow typically involves image or video acquisition, individual detection, feature extraction, and matching against a herd database. In real farm environments, this process can be compromised by variable lighting, partial occlusion, and dynamic herd composition, which may reduce identification accuracy and complicate database maintenance (Hu et al., 2025; Menezes et al., 2025; Xu et al., 2025b). Moreover, reliance on a single biometric modality (e.g., facial or trunk features) may limit robustness under complex farm conditions. Hybrid or multi-modal systems that integrate complementary body-region features represent a promising direction to improve resistance to occlusion and enhance generalization. Future studies should further explore effective fusion strategies and large-scale applicability.

For morphological trait assessment, including body size, body weight, and body condition scoring, the workflow generally consists of multi-view RGB or depth capture, keypoint or landmark detection, metric conversion, and trait calculation. Practical deployment is challenged by motion blur, inconsistent postures, occlusion from neighboring animals or structures, limited multi-breed datasets, and sensor calibration drift (Li et al., 2023a; Bai et al., 2025; Lu et al., 2025; Yang et al., 2025). Future work should emphasize expanding dataset diversity, improving 3D reconstruction algorithms, and developing real-time automated measurement pipelines to enable reliable body assessment across farms and breeds.

For behavioral analysis, the workflow involves continuous video acquisition, multi-animal detection and tracking, temporal modeling, and event classification. Crowded housing, identity switching, low-light conditions, and the need for multi-camera synchronization present significant deployment challenges (Lodkaew et al., 2023; Li et al., 2024a; Wang et al., 2024f; Xu et al., 2025a). Future research should focus on multi-camera fusion, lightweight real-time tracking models, and integration with alert systems to enable early detection of abnormal or welfare-relevant behaviors.

For vital signs monitoring, including heart rate, respiration rate, and body temperature, the workflow relies on sensor capture, ROI localization, signal extraction, and estimation or classification. Deployment challenges include ROI misalignment due to animal movement, variation in fur coverage or dirt, environmental effects such as lighting and temperature, and the need for synchronized multi-sensor data (Shu et al., 2024a; Shu et al., 2024b; Wang et al., 2024a). Future directions should target robust ROI tracking methods, multimodal sensor fusion, and adaptive algorithms to ensure reliable, continuous health monitoring in farm conditions.

For disease detection, including mastitis and lameness, the workflow generally consists of ROI capture, feature extraction, classification, and alert generation. Early-stage disease signs are often subtle, and practical deployment is complicated by occlusion, environmental noise, and variability across barns and breeds (Jabbar et al., 2017; Li et al., 2024c; Gayathri et al., 2025). Future work should emphasize multi-modal feature integration, cross-farm generalization, and the development of early-warning systems to enable timely and accurate detection of health issues at scale.

8. Conclusion

PLF, aiming to enhance production efficiency, ensure animal welfare, and promote sustainable development, has been recognized as an effective approach to strengthening individual-level management and optimizing decision-making. Non-contact monitoring technologies provide new possibilities for intelligent farming by enabling cattle identification, morphological trait assessment, behavioral analysis, vital signs monitoring, and disease detection. This review systematically summarizes research progress on non-contact monitoring in cattle, outlining the core technical pathways and application scenarios to provide a curated reference for future studies and practical implementation. Despite significant advancements, large-scale deployment in real farming environments still faces multiple challenges, including limited data resources, insufficient algorithm generalization, incomplete evaluation frameworks, and low system integration. Future efforts should focus on interdisciplinary collaboration and industrial synergy, particularly the deep integration of animal science and computer vision, to drive the efficient application of existing technologies in cattle monitoring. The joint contributions of researchers, engineers, farm managers, and policymakers are essential to advancing intelligent and sustainable precision cattle farming.

CRediT authorship contribution statement

Xingshi Xu: Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Data curation. **Benhai Xiong:** Writing – review & editing, Validation, Project administration, Formal analysis. **Dong Liu:** Writing – review & editing, Validation, Resources, Investigation, Formal analysis, Data curation. **Tomas Norton:** Writing – review & editing, Visualization, Supervision, Project administration, Investigation. **Huaibo Song:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

References

Achour, B., Belkadi, M., Filali, I., Laghrouche, M., Lahdir, M., 2020. Image analysis for individual identification and feeding behaviour monitoring of dairy cows based on Convolutional Neural Networks (CNN). Biosyst. Eng. 198, 31–49.

Albertí, P., Panea, B., Sañudo, C., Olleta, J., Ripoll, G., Ertbjerg, P., Christensen, M., Gigli, S., Failla, S., Concetti, S., Hocquette, J., Jailler, R., Rude, S., Renand, G., Nute, G., Richardson, R., Williams, J., 2008. Live weight, body size and carcass characteristics of young bulls of fifteen European breeds. Livest. Sci. 114 (1), 19–30.

Allen, A., Golden, B., Taylor, M., Patterson, D., Henriksen, D., Skuce, R., 2008. Evaluation of retinal imaging technology for the identification of bovine animals in Northern Ireland. Livest. Sci. 116 (1–3), 42–52.

Alvarez, J., Arroqui, M., Mangudo, P., Toloza, J., Jatip, D., Rodríguez, J., Teyseyre, A., Sanz, C., Zunino, A., Machado, C., Mateos, C., 2018. Body condition estimation on cows from depth images using Convolutional Neural Networks. Comput. Electron. Agric. 155, 12–22.

Awad, A., Zawbaa, H., Mahmoud, H., Nabi, E., Fayed, R., Hassanien, A. (2013). A robust cattle identification scheme using muzzle print images. Federated conference on computer science and information systems (FedCSIS), Krakow, POLAND.

Bai, L., Guo, C., Song, J., 2025. Cattle weight estimation model through readily photos. Eng. Appl. Artif. Intel. 143, 109976.

Bakhshayeshi, I., Erfani, E., Taghikhah, F., Elbourn, S., Beheshti, A., 2023. An intelligence cattle re-identification system over transport by siamese neural networks and YOLO. IEEE Internet Things J. 11 (2), 3294944.

Bao, Y., Lu, H., Wu, J., Lei, J., Zhang, J., Lou, X., Guo, H., 2023. Rapid and automated body measurement of cattle based on statistical shape model. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. X-1/W1-2023, 541-546.

Bao, Y., Wang, Y., Li, H., Huang, J., Jiang, D., Wang, Z., Lou, T., Wu, Y., Ma, Z., Wu, F., Liu, Z., 2026. Lightweight pruning-driven YOLOv8-PMP for visual detection of pine nut rot. Smart Agric. Technol. 13, 101835.

Bello, R., Talib, A., Mohamed, A., 2021. Deep belief network approach for recognition of cow using cow nose image pattern. Walailak Journal of Science and Technology (WJST). 18 (5), 8984.
Bergamini, L., Porrello, A., Dondona, A., Del Negro, E., Mattioli, M., D'Alterio, N., Calderara, S., 2018. Multi-Views Embedding for Cattle Re-Identification. Las Palmas de Gran Canaria, SPAIN.
Bergman, N., Yitzhaky, Y., Halachmi, I., 2024. Biometric identification of dairy cows via real-time facial recognition. Animal 18 (3), 101079.
Bewley, J., Peacock, A., Lewis, O., Boyce, R., Roberts, D., Coffey, M., Kenyon, S., Schutz, M., 2008. Potential for estimation of body condition scores in dairy cattle from digital images. J. Dairy Sci. 91 (9), 3439–3453.
Bhole, A., Udmale, S., Falzon, O., Azzopardi, G., 2022. CORF3D contour maps with application to Holstein cattle recognition from RGB and thermal images. Expert Syst. Appl. 192, 116354.
Bhujel, A., Wang, Y., Lu, Y., Morris, D., Dangol, M., 2025. A systematic survey of public computer vision datasets for precision livestock farming. Comput. Electron. Agric. 229, 109718.
Blackie, N., Bleach, E., Amory, J., Scaife, J., 2013. Associations between locomotion score and kinematic measures in dairy cows with varying hoof lesion types. J. Dairy Sci. 96 (6), 3564–3572.
Bumbálek, R., Stehlík, R., Zoubek, T., Ufitikirezi, J., Umurungi, S., Kuneš, R., Havelka, Z., Bartoš, P., 2026. Automated detection and localization of hoof diseases in dairy cattle using an integrated computer vision and infrared thermography system. Comput. Electron. Agric. 243, 111404.
Cai, Z., Cui, J., Yuan, H., Cheng, M., 2023. Application and research progress of infrared thermography in temperature measurement of livestock and poultry animals: a review. Comput. Electron. Agric. 205, 107586.
Cangar, Ö., Leroy, T., Guarino, M., Vranken, E., Fallon, R., Lenehan, J., Mee, J., Berckmans, D., 2008. Automatic real-time monitoring of locomotion and posture behaviour of pregnant cows prior to calving using online image analysis. Comput. Electron. Agric. 64, 53–60.
Chen, S., Ge, C., Tong, Z., Wang, J., Song, Y., Wang, J., Luo, P. 2022. AdaptFormer: Adapting vision transformers for scalable visual recognition. arXiv preprint arXiv: 2205.13535.
Chen, X., Dai, B., Wang, X., Li, Y., Fu, X., Dai, X., Xin, H., Li, Y., Shen, W., 2025a. Respiratory rate detection of dairy cows based on infrared thermography in head movement scenarios. J. Therm. Biol 130, 104154.
Chen, Y., Rustia, D.J., Huang, S., Hsu, J., Lin, T., 2025b. IoT-based system for individual dairy cow feeding behavior monitoring using cow face recognition and edge computing. Internet Things 33, 101674.
Cheng, H., Zhang, M., Shi, J., 2024. A survey on deep neural network pruning: taxonomy, comparison, analysis, and recommendations. IEEE Trans. Pattern Anal. Mach. Intell. 46 (12), 10558–10578.
Chiumia, D., Chagunda, M., Macrae, A., Roberts, D., 2012. Predisposing factors for involuntary culling in Holstein–Friesian dairy cows. J. Dairy Res. 80 (1), 45–50.
Chu, M., Li, Q., Wang, Y., Zeng, X., Si, Y., Liu, G., 2023a. Fusion of udder temperature and size features for the automatic detection of dairy cow mastitis using deep learning. Comput. Electron. Agric. 212, 108131.
Chu, M., Liu, X., Zeng, X., Wang, Y., Liu, G., 2023b. Research advances in the automatic detection technology for mastitis of dairy cows. Transactions of the Chinese Society of Agricultural Engineering. 39 (11), 1–12.
Chu, M., Si, Y., Li, Z., Li, Q., Liu, G., 2025. Multi-feature image layers fusion for accurate detection of dairy cow mastitis using deep learning. Comput. Electron. Agric. 239, 110937.
Chung, H., Vu, H., Kim, Y., Choi, C., 2023. Subcutaneous temperature monitoring through ear tag for heat stress detection in dairy cows. Biosyst. Eng. 235, 202–214.
Church, J., Hegadoren, P., Paetkau, M., Miller, C., Regev-Shoshani, G., Schaefer, A., Schwartzkopf-Genswein, K., 2014. Influence of environmental factors on infrared eye temperature measurements in cattle. Res. Vet. Sci. 96 (1), 220–226.
Cíhan, P., Saygili, A., Akyüzlü, M., Özmen, N.E., Ermutlu, C.S., Aydin, U., Yilmaz, A., Aksoy, Ö., 2025a. U-net-based approaches for biometric identification and recognition in cattle. Kafkas Universitesi Veteriner Fakultesi Dergisi. 31 (3), 425–436.
Cihan, P., Saygılı, A., Ermutlu, C. Ş., Akyüzlü, M., Aydın, U., Yılmaz, A., Özmen, N. E., Aksoy, Ö., 2025b. U-Net-based approaches for biometric identification and recognition in cattle. Kafkas Univ. Vet. Fak. Derg. 31(3), 10.9775/kvfd.2025.34130.
Cihan, P., Saygılı, A., Ermutlu, C., Aydın, U., Aksoy, Ö., 2024. AI-aided cardiovascular disease diagnosis in cattle from retinal images: machine learning vs. deep learning models. Comput. Electron. Agric. 226, 109391.
Cominotte, A., Fernandes, A., Dorea, J., Rosa, G., Ladeira, M., van Cleef, E., Pereira, G., Baldassini, W., Neto, O., 2020. Automated computer vision system to predict body weight and average daily gain in beef cattle during growing and finishing phases. Livest. Sci. 232, 103904.
Curti, P., Souza, A., Kobayashi, L., Castanheira, A., Pinto, D., Ruiz, A., Andrietta, L., Balieiro, J., Rennó, F., Sousa, E., Ventura, R., 2025. Respiratory rate regression in Holstein dairy cattle with deep neural networks: an evaluation on different body regions. Comput. Electron. Agric. 239, 110987.
Cuthbertson, H., Tarr, G., González, L.A., 2019. Methodology for data processing and analysis techniques of infrared video thermography used to measure cattle temperature in real time. Comput. Electron. Agric. 167, 105019.
Dabele, D., Borena, B., Admasu, P., Gebremedhin, E., Marami, L., 2021. Prevalence and risk factors of mastitis and isolation, identification and antibiogram of staphylococcus species from mastitis positive zebu cows in toke kutaye, cheliya, and dendi districts, west shewa zone, oromia, ethiopia. Infect. Drug Resist. 14, 987–998.
Dahl, M., De Vries, A., Maunsell, F., Galvao, K., Risco, C., Hernandez, J., 2018. Epidemiologic and economic analyses of pregnancy loss attributable to mastitis in primiparous Holstein cows. J. Dairy Sci. 101 (11), 10142–10150.
de Mol, R., Ouweltjes, W., 2001. Detection model for mastitis in cows milked in an automatic milking system. Prev. Vet. Med. 49 (1–2), 71–82.
de Vires, A., 2006. Economic value of pregnancy in dairy cattle. J. Dairy Sci. 89 (10), 3876–3885.
De Vries, A., Marcondes, M.I., 2020. Review: Overview of factors affecting productive lifespan of dairy cows. Animal 14 (1), s155–s164.
Deng, H., Yang, G., Xu, X., Hua, Z., Liu, J., Song, H., 2025. Fusion of CREStereo and MobileViT-Pose for rapid measurement of cattle body size. Comput. Electron. Agric. 232, 110103.
Denis-Robichaud, J., Kelton, D., Fauteux, Villettaz-Robichaud, M., Dubuc, J., 2020. Short communication: Accuracy of estimation of lameness, injury, and cleanliness prevalence by dairy farmers and veterinarians. J. Dairy Sci. 103(11), 10696-10702.
Devi, I., Singh, N., Dudi, K., Ranjan, R., Lathwal, S., Tomar, S., Nagar, H., 2024. Deep learning aided computer vision system forautomated linear type trait evaluation indairy cows. Smart Agric. Technol. 8, 100509.
Dohmen, R., Catal, C., Liu, Q., 2021. Image-based body mass prediction of heifers using deep neural networks. Biosyst. Eng. 204, 283–293.
Du, A., Guo, H., Lu, J., Su, Y., Ma, Q., Ruchay, A., Marinello, F., Pezzuolo, A., 2022. Automatic livestock body measurement based on keypoint detection with multiple depth cameras. Comput. Electron. Agric. 198, 107059.
Ferguson, J., Azzaro, G., Licitra, G., 2006. Body condition assessment using digital images. J. Dairy Sci. 89 (10), 3833–3841.
Ferreira, R., Bresolin, T., Rosa, G., Dorea, J., 2022. Using dorsal surface for individual identification of dairy calves through 3D deep learning algorithms. Comput. Electron. Agric. 201, 107272.
Flower, F., Sanderson, D., Weary, D., 2005. Hoof pathologies influence kinematic measures of dairy cow gait. J. Dairy Sci. 88 (9), 3166–3173.
Franco, M., Marcondes, M., Campos, J., Freitas, D., Detmann, E., Valadares, F., 2017. Evaluation of body weight prediction Equations in growing heifers. Acta Scientiarum. Animal Sciences. 39 (2), 201–206.
Fuentes, A., Yoon, S., Park, J., Park, D., 2020. Deep learning-based hierarchical cattle behavior recognition with spatio- temporal information. Comput. Electron. Agric. 177, 105627.
Gayathri, S., Bhakat, M., Mohanty, T., Chaturvedi, K., Kumar, R., Gupta, A., Kumar, S., 2024. Udder thermogram-based deep learning approach for mastitis detection in Murrah buffaloes. Comput. Electron. Agric. 220, 105899.
Gayathri, S., Bhakat, M., Mohanty, T., Kumar, R., Chaturvedi, K., Kumar, S., 2025. Deep learning enhanced thermographic modeling for early and precise mastitis detection in Sahiwal cows. Res. Vet. Sci. 196, 105899.
Geng, H., Hou, Z., Liang, J., Li, X., Zhou, X., Xu, A., 2024. Motion focus global-local network: Combining attention mechanism with micro action features for cow behavior recognition. Comput. Electron. Agric. 226, 109399.
Halachmi, I., Klopcic, M., Polak, P., Roberts, D., Bewley, J., 2013. Automatic assessment of dairy cattle body condition score using thermal imaging. Comput. Electron. Agric. 99, 35–40.
Han, S., Fuentes, A., Park, J., Yoon, S., Yang, J., Jeong, Y., Park, D., 2025a. Utilizing farm knowledge for indoor precision livestock farming: Time-domain adaptation of cattle face recognition. Comput. Electron. Agric. 234, 110301.
Han, Y., Wu, J., Zhang, Q., Feng, X., Xu, Y., Zhang, T., Wang, B., Zhang, H., 2025b. ASGP-IDet: Temporal behaviour localisation of beef cattle in untrimmed surveillance videos. Comput. Electron. Agric. 232, 110059.
Hao, W., Han, M., Zhang, K., Zhang, L., Hao, W., Li, F., Liu, Z., 2024. Novel method for the recognition of Jinnan cattle action using bottleneck attention enhanced two-stream neural network. Int. J. Agric. Biol. Eng. 17 (3), 203–210.
Hao, W., Zhang, K., Han, M., Hao, W., Wang, J., Li, F., Liu, Z., 2023. A novel Jinnan individual cattle recognition approach based on mutual attention scheme. Expert Syst. Appl. 230, 120551.
Heinrichs, A., Rogers, G., Cooper, J., 1992. Predicting body-weight and wither height in holstein heifers using body measurements. J. Dairy Sci. 75 (12), 3576–3581.
Higaki, S., Matsui, Y., Miwa, M., Yamamura, T., Hojo, T., Yoshioka, K., Vang, A., Negreiro, A., Dorea, J.R.R., 2024. Leveraging computer vision-based pose estimation technique in dairy cows for objective mobility analysis and scoring system. Comput. Electron. Agric. 217, 108573.
Hossain, M., Kabir, M., Zheng, L., Swain, D., McGrath, S., Medway, J., 2022. A systematic review of machine learning techniques for cattle identification: Datasets, methods and future directions. Artif. Intell. Agric. 6, 138–155.
Hossein-Zadeh, N., 2025. Artificial intelligence in veterinary and animal science: applications, challenges, and future prospects. Comput. Electron. Agric. 235, 110395.
Hou, Z., Huang, L., Zhang, Q., Miao, Y., 2023. Body weight estimation of beef cattle with 3D deep learning model: PointNet++. Comput. Electron. Agric. 213, 108184.
Hou, Z., Zhang, Q., Zhang, B., Zhang, H., Huang, L., Wang, M., 2025. CattlePartNet: an identification approach for key region of body size and its application on body measurement of beef cattle. Comput. Electron. Agric. 232, 110013.
Hu, H., Dai, B., Shen, W., Wei, X., Sun, J., Li, R., Zhang, Y., 2020. Cow identification based on fusion of deep parts features. Biosyst. Eng. 192, 245–256.
Hu, H., Mu, T., Ma, Y., Wang, X., Ma, Y., 2021. Analysis of Longevity Traits in Holstein cattle: a Review. Front. Genet. 12, 695543.
Hu, L., Li, X., Li, G., Wang, Z., 2025. AngusRecNet: Multi-module cooperation for facial anti-occlusion recognition in single-stage Angus cattle. Comput. Electron. Agric. 236, 110456.

Hua, Z., Wang, Z., Xu, X., Kong, X., Song, H., 2023. An effective PoseC3D model for typical action recognition of dairy cows based on skeleton features. Comput. Electron. Agric. 212, 108152.

Hyodo, R., Nakano, T., Ogawa, T., 2020. Feature representation learning for calving detection of cows using video frames. International Conference on Pattern Recognition. 4131–4136.

Jabbar, K., Hansen, M., Smith, M., Smith, L., 2017. Early and non-intrusive lameness detection in dairy cows using 3-dimensional video. Biosyst. Eng. 153, 63–69.

Jensen, M., 2012. Behaviour around the time of calving in dairy cows. Appl. Anim. Behav. Sci. 139, 195–202.

Jiang, B., Song, H., Wang, H., Li, C., 2022. Dairy cow lameness detection using a back curvature feature. Comput. Electron. Agric. 194, 106729.

Jiang, B., Yin, X., Song, H., 2020. Single-stream long-term optical flow convolution network for action recognition of lameness dairy cow. Comput. Electron. Agric. 175, 105536.

Jing, X., Wu, T., Shen, P., Chen, Z., Jia, H., Song, H., 2025. In situ volume measurement of dairy cattle via neural radiance fields-based 3D reconstruction. Biosyst. Eng. 250, 105–116.

Kandeel, S., Megahed, A., Ebeid, M., Constable, P., 2019. Evaluation of 3 esterase tests for the diagnosis of subclinical mastitis at dry-off and freshening in dairy cattle. J. Dairy Sci. 102 (2), 1402–1416.

Kang, X., Li, S., Li, Q., Liu, G., 2022. Dimension-reduced spatiotemporal network for lameness detection in dairy cows. Comput. Electron. Agric. 197, 106922.

Kastberger, G., Stachl, R., 2003. Infrared imaging technology and biological applications. Behav. Res. Methods Instrum. Comput. 35, 429–439.

Kaur, A., Kumar, M., Jindal, M., 2022. Cattle identification with muzzle pattern using computer vision technology: a critical review and prospective. Soft. Comput. 26 (10), 4771–4795.

Kemp, M., Nolan, A., Cripps, P., Fitzpatrick, J., 2008. Animal-based measurements of the severity of mastitis in dairy cows. Vet. Rec. 163 (6), 175–179.

Kerbrat, S., Disenhaus, C., 2004. A proposition for an updated behavioural characterisation of the oestrus period in dairy cows. Appl. Anim. Behav. Sci. 87 (3–4), 223–238.

Khakimov, A., Pavkin, D., Yurochka, S., Astashev, M., Dovlatov, I., 2022. Development of an algorithm for rapid herd evaluation and predicting milk yield ofmastitis cows based on infrared thermography. Appl. Sci.-Basel 12 (13), 6621.

Khin, M., Tin, P., Horii, Y., Zin, T.T., 2024. Predictive modeling of cattle calving time emphasizing abnormal and normal cases by using posture analysis. Sci. Rep. 14, 31871.

Kim, H., Choi, H., Lee, D., Yoon, Y., 2005a. Recognition of individual Holstein cattle by imaging body patterns. Asian-Australas. J. Anim. Sci. 18 (8), 1194–1198.

Kim, H., Ikeda, Y., Choi, H., 2005b. The identification of Japanese black cattle by their faces. Asian-Australas. J. Anim. Sci. 18 (6), 868–872.

Kim, S., Hidaka, Y., 2021. Breathing pattern analysis in cattle using infrared thermography and computer vision. Animals 11 (1), 207.

Kim, S., Yamagishi, N., Ishikawa, S., Tsuchiaka, S., 2025. Unique temperature change patterns in calves eyes and muzzles: a non-invasive approach using infrared thermography and object detection. Front. Vet. Sci. 12, 1548906.

Köhler, A., Scholz, A., Kremer-Rücker, P., 2025. Tail tip temperature measured by thermography as an indicator of animal health in Holstein cows. Animal 19 (10), 101621.

Korelidou, V., Simitzis, P., Massouras, T., Gelasakis, A., 2024. Infrared thermography as a diagnostic tool for the assessment of mastitis in dairy ruminants. Animals 14 (18), 2691.

Krogstad, K., Bradford, B., 2025. Associations of body condition score, body condition score change, and hyperketonemia with mastitis, reproduction, and milk production. J. Dairy Sci. 108 (3), 2808–2819.

Krpálková, L., O'Mahony, N., Carvalho, A., Campbell, S., Walsh, J., 2020. Evaluating the economic profit of reproductive performance through the integration of a dynamic programming model on a specific dairy farm. Czech J. Anim. Sci. 65 (04), 124–134.

Kumar, N., Singh, S., 2026. Multi-directional shifted patch encoding with transformers for non-invasive cattle identification. IEEE Trans. Biom. Behav. Identity Sci. 7 (4), 620–631.

Kumar, S., Singh, S., Abidi, A., Datta, D., Sangaiah, A., 2018. Group sparse representation approach for recognition of cattle on muzzle point images. Int. J. Parallel Prog. 46 (5), 812–837.

Kusakunniran, W., Wiratsudakul, A., Chuachan, U., Kanchanapreechakorn, S., Imaromkul, T., Suksriupatham, N., Thongkanchorn, K., 2020. Biometric for cattle identification using muzzle patterns. Int. J. Pattern Recognit Artif Intell. 34 (12), 2056007.

Le Cozler, Y., Allain, C., Caillot, A., Delouard, J.M., Delattre, L., Luginbuhl, T., Faverdin, P., 2019a. High-precision scanning system for complete 3D cow body shape imaging and analysis of morphological traits. Comput. Electron. Agric. 157, 447–453.

Le Cozler, Y., Allain, C., Xavier, C., Depuille, L., Caillot, A., Delouard, J.M., Delattre, L., Luginbuhl, T., Faverdin, P., 2019b. Volume and surface area of Holstein dairy cows calculated from complete 3D shapes acquired using a high-precision scanning system: interest for body weight estimation. Comput. Electron. Agric. 165, 1–29.

Li, D., Dai, B., Li, Y., Song, P., Dai, X., He, Y., Liu, H., Li, Y., Shen, W., 2024a. IATEFF-YOLO: Focus on cow mounting detection during nighttime. Biosyst. Eng. 246, 54–66.

Li, G., Erickson, G., Xiong, Y., 2022a. Individual beef cattle identification using muzzle images and deep learning techniques. Animals 12 (11), 1453.

Li, J., Ma, W., Bai, Q., Tulpan, D., Gong, M., Sun, Y., Xue, X., Zhao, C., Li, Q., 2023a. A posture-based measurement adjustment method for improving the accuracy of beef cattle body size measurement based on point cloud data. Biosyst. Eng. 230, 171–190.

Li, J., Zeng, P., Yue, S., Zheng, Z., Qin, L., Song, H., 2025a. Automatic body condition scoring system for dairy cows in group state based on improved YOLOv5 and video analysis. Artif. Intell. Agric. 15 (2), 350–362.

Li, Q., Chu, M., Kang, X., Liu, G., 2023b. Temporal aggregation network using micromotion features for early lameness recognition in dairy cows. Comput. Electron. Agric. 204, 107562.

Li, Q., He, Z., Liu, X., Chu, M., Wang, Y., Kang, X., Liu, G., 2024b. Lameness detection system for dairy cows based on instance segmentation. Expert Syst. Appl. 249, 123775.

Li, Q., Si, Y., Chu, M., Kang, X., Liu, G., 2024c. Lameness detection of dairy cows based on key frame positioning and posture analysis. Comput. Electron. Agric. 227, 109537.

Li, Q., Si, Y., Chu, M., Liu, N., Kang, X., Liu, G., 2024d. A novel lameness detection method for dairy cows based on temporal gait and spatial post features. Comput. Electron. Agric. 224, 109172.

Li, R., Wen, Y., Zhang, S., Xu, X., Ma, B., Song, H., 2024e. Automated measurement of beef cattle body size via key point detection and monocular depth estimation. Expert Syst. Appl. 244, 123042.

Li, W., Ji, Z., Wang, L., Sun, C., Yang, X., 2017. Automatic individual identification of Holstein dairy cows using tailhead images. Comput. Electron. Agric. 142, 622–631.

Li, X., Hu, Z., Huang, X., Feng, T., Yang, X., Li, M. (2019). Cow body condition score estimation with convolutional neural networks. 2019 IEEE 4th International Conference on Image, Vision and Computing (ICIVC), Xiamen, China, IEEE.

Li, Z., Lei, X., Liu, S., 2022b. A lightweight deep learning model for cattle face recognition. Comput. Electron. Agric. 195, 106848.

Li, Z., Sun, H., Guo, Q.H., Zhang, H., Liu, H., 2025b. Research progress on machine vision technology for non-contact body measurement of large livestock. Transactions of the Chinese Society of Agricultural Engineering. 41 (7), 1–12.

Li, Z., Zhang, Q., Lv, S., Han, M., Jiang, M., Song, H., 2022c. Fusion of RGB, optical flow and skeleton features for the detection of lameness in dairy cows. Biosyst. Eng. 218, 62–77.

Little, M., Weller, J., Buijs, S., 2025. The impact of the dairy cow's position on eye and udder temperatures obtained with infra-red thermography within a walk-trough system. Animal 19 (6), 101523.

Lodkaew, T., Pasupa, K., Loo, C., 2023. CowXNet: an automated cow estrus detection system. Expert Syst. Appl. 211, 118550.

Louca, A., J., L., 1968. Production losses in dairy cattle due to days open. J. Dairy Sci. 51 (4), 537-583.

Lovarelli, D., Bacenetti, J., Guarino, M., 2020. A review on dairy cattle farming: is precision livestock farming the compromise for an environmental, economic and social sustainable production? J. Clean. Prod. 262, 121409.

Lowe, G., Sutherland, M., Waas, J., Schaefer, A., Cox, N., Stewart, M., 2019. Infrared thermography-s non-invasive method of measuring respiration rate in calves. Animals 9 (8), 535.

Lu, H., Zhang, J., Yuan, X., Lv, J., Zeng, Z., Guo, H., Ruchay, A., 2025. Automatic coarse-to-fine method for cattle body measurement based on improved GCN and 3D parametric model. Comput. Electron. Agric. 231, 110017.

Lu, Y., Weng, Z., Zheng, Z., Zhang, Y., Gong, C., 2023. Algorithm for cattle identification based on locating key area. Expert Syst. Appl. 228, 120365.

Luo, X., Hu, Y., Gao, Z., Damjin, B., Guo, H., Ruchay, A. (2022). Construction of statistical shape model of real cattle and its application to body measurement. 2022 IEEE Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), Perugia, Italy.

Luo, X., Hu, Y., Gao, Z., Guo, H., Su, Y., 2023. Automated measurement of livestock body based on pose normalisation using statistical shape model. Biosyst. Eng. 227, 36–51.

Luo, Y., Gui, N., Yang, X., Tu, J., Jiang, S., 2025. An analytical model for the three-dimensional thermal resistance of particles considering internal heat conduction based on the generalized thermal resistance concept. Int. J. Heat Mass Transf. 240, 126619.

Ma, F., Li, D., Chen, Y., Xing, J., Liu, Y., Lan, D., Shao, J., Pang, Z., 2025. Orchestrating embodied systems through the embodied context protocol: motivation, progress, and directions. Research 8, 1047.

Ma, S., Zhang, Q., Li, T., Song, H., 2022. Basic motion behavior recognition of single dairy cow based on improved Rexnet 3D network. Comput. Electron. Agric. 194, 106772.

Mahato, S., Neethirajan, S., 2025. Integrating artificial intelligence in dairy farm management - biometric facial recognition for cows. Information Processing in Agriculture. 10, 1–14.

Mahmud, M., Zahid, A., Das, A., Muzammil, M., Khan, M., 2021. A systematic literature review on deep learning applications for precision cattle farming. Comput. Electron. Agric. 187, 106313.

Mantovani, P., Menezes, G., Dórea, J., 2024. Predicting respiration rate in unrestrained dairy cows using image analysis and fast Fourier transform. JDS Communications. 5, 310–316.

Manzoor, S., Syed, Z., Abubabakar, M., 2023. Global perspectives of intensive animal farming and its applications. Intech Open. 10, 112271.

Maw, S., Zin, T., Tin, P., Kobayashi, I., Horii, Y., 2021. An absorbing markov chain model to predict dairy cow calving time. Sensors 21 (19), 6490.

McManus, C., Tanure, B., Peripolli, V., Seixas, L., Fischer, V., Gabbi, A., Menegassi, S., Stumpf, M., Kolling, G., DIasi, E., Costa Jr, J., 2016. Infrared thermography in animal production: An overview. Comput. Electron. Agric. 123, 10-16.

Menezes, G., Alves, A., Negreiro, A., Ferreira, R., Higaki, S., Casella, E., Rosa, G., Dorea, J., 2025. Color-independent cattle identification using keypoint detection and Siamese neural networks in closed- and open-set scenarios. J. Dairy Sci. 108 (9), 9662–9680.

Metzner, M., Sauter-Louis, C., Seemueller, A., Petzl, W., Zerbe, H., 2015. Infrared thermography of the udder after experimentally induced *Escherichia coli* mastitis in cows. Vet. J. 204 (3), 360–362.

Mg, H., Tin, P., Aikawa, W., Kazuyuki, H., Horii, Y., Zin, T., 2026. Signal-based feature analysis of behavioral trajectories for predicting calving time and classifying assistance needs. Comput. Electron. Agric. 243, 111301.

Mg, W., Zin, T.T., Tin, P., Aikawa, M., Honkawa, K., Horii, Y., 2025. Automated system for calving time prediction and cattle classification utilizing trajectory data and movement features. Sci. Rep. 15 (1), 2378.

Miedema, H., Cockram, M., Dwyer, C., Macrae, A., 2011. Behavioural predictors of the start of normal and dystocic calving in dairy cows and heifers. Appl. Anim. Behav. Sci. 132, 14–19.

Miller, G., Hyslop, J., Barclay, D., Edwards, A., Thomson, W., Duthie, C., 2019. Using 3D imaging and machine learning to predict liveweight and carcass characteristics of live finishing beef cattle. Front. Sustainable Food Syst. 3, 1–9.

Min, X., Sok, J., Qian, T., Zhou, W., Lansink, A., 2025. Evaluating the adoption of sensor and robotic technologies from a multi-stakeholder perspective: the case of greenhouse sector in China. Technol. Forecast. Soc. Chang. 210, 123842.

Moe, A., Tin, P., Aikawa, M., Kobayashi, I., Zin, T., 2025. AI-powered visual E-monitoring system for cattle health and wealth. Smart Agric. Technol. 12, 101300.

Murugeswari, S., Murugan, K., Rajathi, S., Kumar, M., 2022. Monitoring body temperature of cattle using an innovative infrared photodiode thermometer. Comput. Electron. Agric. 198, 107120.

Nasir, M.F., Fuentes, A., Han, F., Liu, J., Jeong, Y., Yoon, S., Park, D., 2025. Multi-camera fusion and bird-eye view location mapping for deep learning-based cattle behavior monitoring. Artif. Intell. Agric. 15 (4), 724–743.

Neethirajan, S., Kemp, B., 2021. Digital Livestock Farming. Sens. Bio-Sens. Res. 32, 100408.

Nir, O., Parmet, Y., Werner, D., Adin, G., Halachmi, I., 2018. 3D Computer-vision system for automatically estimating heifer height and body mass. Biosyst. Eng. 173, 4–10.

Norton, T., Chen, C., Larsen, M., Berckmans, D., 2019. Precision livestock farming: building 'digital representations' to bring the animals closer to the farmer. Animal 13 (12), 3009–3017.

Olechnowicz, J., Jaśkowski, J., 2011. Reasons for culling, culling due to lameness,and economic losses in dairy cows. Med. Weter. 67 (9), 618–621.

Pan, D., Mo, T., Jiang, Z., Duan, Y., Li, Z., Maldague, X., 2025. Interference factors and compensation methods when using infrared thermography for temperature measurement: a review. IEEE Trans. Instrum. Meas. 74, 1015124.

Pathak, P., Parakash, S., 2026. Enhancing digital cattle identification with fine-grained image analysis. Expert Syst. Appl. 297 (1), 129409.

Peng, Y., Peng, Z., Zou, H., Liu, M., Hu, R., Xiao, J., Liao, H., Yang, Y., Huo, L., Wang, Z., 2024. A dynamic individual method for yak heifer live body weight estimation using the YOLOv8 network and body parameter detection algorithm. J. Dairy Sci. 107 (8), 6178–6191.

Pluk, A., Bahr, C., Leroy, T., Poursaberi, A., Song, X., Vranken, E., Maertens, W., Van Nuffel, A., D., B., 2010. Evaluation of step overlap as an automatic measure in dairy cow locomotion. Transactions of the American Society of Agricultural and Biological Engineers. 53(4), 1305-1312.

Porto, S., Arcidiacono, C., Anguzza, U., Cascone, G., 2013. A computer vision-based system for the automatic detection of lying behaviour of dairy cows in free-stall barns. Biosyst. Eng. 115 (2), 184–194.

Porto, S., Arcidiacono, C., Anguzza, U., Cascone, G., 2015. The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. Biosyst. Eng. 133, 46–55.

Poursaberi, A., Bahr, C., Pluk, A., Van Nuffel, A., Berckmans, D., 2010. Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques. Comput. Electron. Agric. 74 (1), 110–119.

Prus, I., Weber, S., Ostrensky, A., Daros, R., Ollhoff, R., Sotomaior, C., 2025. Evaluation of sensor measurements for early identification of clinical mastitis in an automatic milking system. J. Dairy Res. 18, 1–7.

Pu, L., Zhao, Y., Kang, H., Kong, X., Du, X., Song, H., 2025. DenseDFFNet: Dense connected dual-stream feature fusion network for calf manure segmentation and diarrhea recognition. Comput. Electron. Agric. 234, 110328.

Qiao, Y., Guo, Y., Yu, K., He, D., 2022. C3D-ConvLSTM based cow behaviour classification using video data for precision livestock farming. Comput. Electron. Agric. 193, 106650.

Qiao, Y., Kong, H., Clark, C., Lomax, S., Su, D., Eiffert, S., Sukkarieh, S., 2021. Intelligent perception for cattle monitoring: a review for cattle identification, body condition score evaluation, and weight estimation. Comput. Electron. Agric. 185, 106143.

Rahman, Z., Abbasi, M., Ibrahim, H., 2025. Advancing animal farming with deep learning: a systematic review. Comput. Electron. Agric. 237, 110674.

Robcis, R., Ferchiou, A., Berrada, M., Ndiaye, Y., Herman, N., Lhermie, G., Raboisson, D., 2023. Cost of lameness in dairy herds: an integrated bioeconomic modeling approach. J. Dairy Sci. 106 (4), 2519–2534.

Roelofs, J., Lopez-Gatius, F., Hunter, R., Eerdenburg, F., Hanzen, C., 2010. When is a cow in estrus? Clinical and Practical Aspects. Theriogenology. 74 (3), 327–344.

Ruchay, A., Kober, V., Dorofeev, K., Kolpakov, V., Miroshnikov, S., 2020. Accurate body measurement of live cattle using three depth cameras and non-rigid 3-D shape recovery. Comput. Electron. Agric. 179, 105821.

Russello, H., Tol, R., Kooistra, G., 2022. T-LEAP: Occlusion-robust pose estimation of walking cows using temporal information. Comput. Electron. Agric. 192, 106559.

Russello, H., van der Tol, R., Holzhauer, M., van Henten, E., Kootstra, G., 2024. Video-based automatic lameness detection of dairy cows using pose estimation and multiple locomotion traits. Comput. Electron. Agric. 223, 109040.

Sakir, T., Abdullah, U., Seref, U., 2011. Determination of body measurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis. Comput. Electron. Agric. 76 (2), 189–197.

Salau, J., Haas, J., Junge, W., Thaller, G., 2017. A multi-Kinect cow scanning system: calculating linear traits from manually marked recordings of Holstein-Friesian dairy cows. Biosyst. Eng. 157, 92–98.

Sapkota, R., Qureshi, R., Hadi, M., Hassan, S., Sadak, F., Shoman, M., 2025. Multi-modal LLMs in agriculture: a comprehensive review. IEEE Trans. Autom. Sci. Eng. 23, 1–33.

Saygili, A., Cihan, P., Ermutlu, C., Aydin, U., Aksoy, O., 2024. CattNIS: Novel identification system of cattle with retinal images based on feature matching method. Comput. Electron. Agric. 221, 108963.

Senger, P.L., 1994. The estrus detection problem: new concepts, technologies, and possibilities. J. Dairy Sci. 77 (9), 2745–2753.

Sharma, A., Randewich, L., Andrew, W., Hannuna, S., Campbell, N., Mullan, S., Dowsey, A., Smith, M., Hansen, M., Burghardt, T., 2025. Universal bovine identification via depth data and deep metric learning. Comput. Electron. Agric. 229, 109657.

Shen, W., Sun, Y., Zhang, Y., Fu, X., Hou, H., Kou, S., Zhang, Y., 2021. Automatic recognition method of cow ruminating behaviour based on edge computing. Comput. Electron. Agric. 191, 106495.

Sheng, K., Foris, B., von Keyserlingk, M., Timbers, T., Cabrera, V., Weary, D., 2025. Redefining lameness assessment: Constructing lameness hierarchy using crowd-sourced data. Comput. Electron. Agric. 234, 110206.

Shi, W., Dai, B., Shen, W., Sun, Y., Zhao, K., Zhang, Y., 2023. Automatic estimation of dairy cow body condition score based on attention-guided 3D point cloud feature extraction. Comput. Electron. Agric. 206, 107666.

Shipka, M., 2000. A note on silent ovulation identified by using radiotelemetry for estrous detection. Appl. Anim. Behav. Sci. 66 (1–2), 153–159.

Shojaeipour, A., Falzon, G., Kwan, P., Hadavi, N., Cowley, F., Paul, D., 2021. Automated muzzle detection and biometric identification via Few-Shot deep transfer learning of mixed breed cattle. Agronomy-Basel 11 (11), 2365.

Shu, H., Bindelle, J., Gu, X., 2024a. Non-contact respiration rate measurement of multiple cows in a free-stall barn using computer vision methods. Comput. Electron. Agric. 218, 108678.

Shu, H., Bindelle, J., Guo, L., Gu, X., 2023. Determining the onset of heat stress in a dairy herd based on automated behaviour recognition. Biosyst. Eng. 226, 238–251.

Shu, H., Wang, K., Guo, L., Bindelle, J., Wang, W., 2024b. Automated collection of facial temperatures in dairy cows via improved UNet. Comput. Electron. Agric. 220, 108614.

Silper, B., Robles, I., Madureira, A., Burnett, T., Reis, M., Passille, A., de Rushen, J., Cerri, R., 2015. Automated and visual measurements of estrous behavior and their sources of variation in Holstein heifers. I: walking activity and behavior frequency. Theriogenology 84 (2), 312–320.

Song, X., Bokkers, E., van der Tol, P., Koerkamp, P., van Mourik, S., 2018. Automated body weight prediction of dairy cows using 3-dimensional vision. J. Dairy Sci. 101 (5), 4448–4459.

Song, X., Bokkers, E., Van Mourik, S., Groot Koerkamp, P., Van der Tol, P., 2019. Automated body condition scoring of dairy cows using 3-dimensional feature extraction from multiple body regions. J. Dairy Sci. 102 (5), 4294–4308.

Song, X., Leroy, T., Vranken, E., Maertens, W., Sonck, B., Berckmans, D., 2008. Automatic detection of lameness in dairy cattle - Vision-based trackway analysis in cow's locomotion. Comput. Electron. Agric. 64 (1), 39–44.

Spana, Gauttam, H., Chauhan, V., Pattanaik, K., Trivedi, A., Ghosh, H., 2026. A comprehensive review of Edge computing empowered smart agriculture: Trends, opportunities and future directions. Comput. Electron. Agric. 241, 111252.

Spoliansky, R., Edan, Y., Parmet, Y., Halachmi, I., 2016. Development of automatic body condition scoring using a low-cost 3-dimensional Kinect camera. J. Dairy Sci. 99 (9), 7714–7723.

Sprecher, D., Hostetler, D., Kaneene, J., 1997. A lameness scoring system that uses posture and gait to predict dairy cattle reproductive performance. Theriogenology 47 (6), 1179–1187.

Stanek, P., Zólkiewski, P., Janus, E., 2024. A review on mastitis in dairy cows research: current status and future perspectives. Agriculture-Basel 14 (8), 1292.

Stewart, M., Wilson, M., Schaefer, A., Huddart, F., Sutherland, M., 2019. The use of infrared thermography and accelerometers for remote monitoring of dairy cow health and welfare. J. Dairy Sci. 100, 3893–3901.

Sumi, K., Maw, S., Zin, T., Tin, P., Kobayashi, I., Horii, Y., 2021. Activity-integrated hidden markov model to predict calving time. Animals 11 (2), 385.

Sun, Y., Huo, P., Wang, Y., Cui, Z., Li, Y., Dai, B., Li, R., Zhang, Y., 2019. Automatic monitoring system for individual dairy cows based on a deep learning framework that provides identification via body parts and estimation of body condition score. J. Dairy Sci. 102 (11), 10140–10151.

Sutter, J., Lewis, O., Robinson, C., McMahon, A., Boyce, R., Bragg, R., Macrae, A., Orton, J., Shah, V., Ingleby, S., Griffin, P., Riis, E., 2020. Recording the heart beat of cattle using a gradiometer system of optically pumped magnetometers. Comput. Electron. Agric. 177, 105651.

Suzuki, S., Ogasawara, H., Fujimoto, R., Kiyokawa, Y., Takeuchi, Y., 2024. Mounting exhibited between cows is not associated with sexual motivation. Physiol. Behav. 287, 114710.

Swartz, D., Shepley, E., Caixeta, L., Cramer, G., 2025. A descriptive analysis of inter- and intraobserver agreement of body condition scoring methods in dairy cattle. J. Dairy Sci. 108 (9), 9712–9727.

Temesgen, M., Assen, A., Gizaw, T., Minalu, B., Mersha, A., 2022. Factors affecting calving to conception interval (days open) in dairy cows located at Dessie and Kombolcha towns. Ethiopia. Plos ONE. 17 (2), e0264029.

Tenhagen, B., Heuwieser, W., 2006. Mastitis in beef cows - Incidence, pathogens and economic significance - a literature review. Praktische Tierarzt. 87 (9), 708–712.
Thomsen, P., Shearer, J., Houe, H., 2023. Prevalence of lameness in dairy cows: a literature review. Vet. J. 295, 105975.
Tommasoni, C., Fiore, E., Lisuzzo, A., Gianesella, M., 2023. Mastitis in dairy cattle: On-farm diagnostics and future perspectives. Animals 13 (15), 2538.
Tsai, D., Huang, C., 2014. A motion and image analysis method for automatic detection of estrus and mating behavior in cattle. Comput. Electron. Agric. 104, 25–31.
Tuan, S., Rustia, D., Hsu, J., Lin, T., 2022. Frequency modulated continuous wave radar-based system for monitoring dairy cow respiration rate. Comput. Electron. Agric. 196, 106913.
Tun, S., Tsubasa, O., Tin, P., Aikawa, M., Kobayashi, I., Zin, T., 2024. Revolutionizing cow welfare monitoring: a novel top-view perspective with depth camera-based lameness classification. J. Imaging. 10 (3), 67.
Velasco-Bolaños, J., Ceballes-Serrano, C., Velásquez-Mejía, D., Riaño-Rojas, J., Giraldo, C., Carmona, J., Ceballos-Márquez, A., 2021. Application of udder surface temperature by infrared thermography for diagnosis of subclinical mastitis in Holstein cows located in tropical highlands. J. Dairy Sci. 104 (9), 10310–10323.
Vu, H., Prabhume, O., Raskar, U., Panditharatne, D., Chung, H., Choi, C., Kim, Y., 2024. MmCows: a multimodal dataset for dairy cattle monitoring. Adv. Neural Inf. Proces. Syst. 37, 59451–59467.
Wang, F., Zou, X., Chen, Z., Tang, Q., Li, T., Wang, S., Yang, L., Tang, D., 2025a. Non-contact weight intelligent estimation based on yak skeleton localization. Eng. Appl. Artif. Intel. 161, 112036.
Wang, M., Li, S., Peng, R., Räisänen, S., Serviento, A., Sun, X., Wang, K., Yu, F., Niu, M., 2024a. Learning end-to-end respiratory rate prediction of dairy cows from red, green, and blue videos. J. Dairy Sci. 107 (11), 9862–9874.
Wang, M., Youssef, A., Larsen, M., Rault, J., Berckmans, D., Marchant-Forde, J., Hartung, J., Bleich, A., Lu, M., Norton, T., 2021. Contactless video-based heart rate monitoring of a resting and an anesthetized pig. Animals 11 (2), 442.
Wang, R., Bai, Q., Gao, R., Li, Q., Zhao, C., Li, S., Zhang, H., 2022a. Oestrus detection in dairy cows by using atrous spatial pyramid and attention mechanism. Biosyst. Eng. 223, 259–276.
Wang, R., Gao, R., Li, Q., Zhao, C., Ru, L., Ding, L., Yu, L., Ma, W., 2024b. An ultra-lightweight method for individual identification of cow-back pattern images in an open image set. Expert Syst. Appl. 249, 123529.
Wang, R., Li, Y., Tian, F., Liu, Y., Wang, Z., Yuan, C., Lu, X., 2025b. Estrus detection in dairy cows using advanced object tracking and behavioral analysis technologies. Comput. Electron. Agric. 235, 110331.
Wang, X., Chen, B., Yang, R., Liu, K., Cuan, K., Cao, M., 2024c. A non-contact and fast estimating method for respiration rate of cows using machine vision. Agriculture 14 (40), 1–15.
Wang, Y., Chu, M., Kang, X., Liu, G., 2024d. A deep learning approach combining DeepLabV3+and improved YOLOv5 to detect dairy cow mastitis. Comput. Electron. Agric. 216, 108507.
Wang, Y., Kang, X., He, Z., Feng, Y., Liu, G., 2022b. Accurate detection of dairy cow mastitis with deep learning technology: a new and comprehensive detection method based on infrared thermal images. Animal 16 (10), 100646.
Wang, Y., Li, R., Wang, Z., Hua, Z., Jiao, Y., Duan, Y., Song, H., 2023a. E3D: an efficient 3D CNN for the recognition of dairy cow's basic motion behavior. Comput. Electron. Agric. 205, 107607.
Wang, Y., Mücher, S., Wang, K., Wang, W., Kooistra, L., 2025c. Deep metric learning for individual cattle identification using coat patterns: Proposal for a best practice. Comput. Electron. Agric. 238, 110754.
Wang, Y., Wang, X., Liu, K., Cuan, K., Hua, Z., Li, K., Wang, K., 2025d. Non-invasive monitoring for precision sheep farming: Development, challenges, and future perspectives. Comput. Electron. Agric. 231, 110051.
Wang, Y., Xu, X., Wang, Z., Li, R., Hua, Z., Song, H., 2023b. ShuffleNet-Triplet: a lightweight re-identification network for dairy cows in natural scenes. Comput. Electron. Agric. 205, 107632.
Wang, Y., Xu, X., Zhang, S., Wen, Y., Pu, L., Zhao, Y., Song, H., 2024e. Adaptive group sample with central momentum contrast loss for unsupervised individual identification of cows in changeable conditions. Appl. Soft Comput. 167, 112340.
Wang, Y., Yuan, X., Wei, B., Ruchay, A., Pezzuolo, A., Guo, H., 2026. Performance evaluation of a state-of-the-art keypoint detection method for precision livestock farming. Comput. Electron. Agric. 240, 111230.
Wang, Z., Deng, H., Zhang, S., Xu, X., Wen, Y., Song, H., 2025e. Detection and tracking of oestrus dairy cows based on improved YOLOv8n and TransT models. Biosyst. Eng. 252, 61–76.
Wang, Z., Hua, Z., Wen, Y., Zhang, S., Xu, X., Song, H., 2024f. E-YOLO: Recognition of estrus cow based on improved YOLOv8n model. Expert Syst. Appl. 238, 122212.
Wangchuk, K., Wangdi, J., Mindu, M., 2018. Comparison and reliability of techniques to estimate live cattle body weight. J. Appl. Anim. Res. 46 (1), 349–352.
Wathes, C., Kristensen, H., Aerts, J., Berckmans, D., 2008. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? Comput. Electron. Agric. 64 (1), 2–10.
Watz, S., Petzl, W., Zerbe, H., Rieger, A., Glas, A., Schröter, W., Landgraf, T., Metzner, M., 2019. Technical note: Automatic evaluation of infrared thermal images by computerized active shape modeling of bovine udders challenged with *Escherichia coli*. J. Dairy Sci. 102 (5), 4541–4545.
Weber, V., Weber, F., Oliveira, A., Astolfi, G., Menezes, G., Porto, V., Rezende, F., de Moraes, P., Matsubara, E., Mateus, R., de Araujo, T., da Silva, L., de Queiroz, E., de Abreu, U., Gomes, R., Pistori, H., 2020. Cattle weight estimation using active contour models and regression trees Bagging. Comput. Electron. Agric. 179, 105804.
Weng, Z., Lu, Y., Zheng, Z., Wang, M., Zhang, Y., Gong, C., 2025. Cattle incremental learning identification method based on phased dynamic expansion network. Expert Syst. Appl. 285, 128019.
Weng, Z., Meng, F., Liu, S., Zhang, Y., Zheng, Z., Gong, C., 2022. Cattle face recognition based on a Two-Branch convolutional neural network. Comput. Electron. Agric. 196, 106871.
Wildman, E., Jones, G., Wagner, P., Boman, R., Troutt, H., Lesch, T., 1982. A dairy cow body condition scoring system and its relationship to selected production characteristics. J. Dairy Sci. 65 (3), 495–501.
Wu, D., Han, M., Song, H., Song, L., Duan, Y., 2023. Monitoring the respiratory behavior of multiple cows based on computer vision and deep learning. J. Dairy Sci. 106 (4), 2963–2979.
Wu, D., Wang, Y., Han, M., Song, L., Shang, Y., Zhang, X., Song, H., 2021. Using a CNN-LSTM for basic behaviors detection of a single dairy cow in a complex environment. Comput. Electron. Agric. 182, 106016.
Wu, D., Wu, Q., Yin, X., Jiang, B., Wang, H., He, D., Song, H., 2020a. Lameness detection of dairy cows based on the YOLOv3 deep learning algorithm and a relative step size characteristic vector. Biosyst. Eng. 189, 150–163.
Wu, D., Yin, X., Jiang, B., Jiang, M., Li, Z., Song, H., 2020b. Detection of the respiratory rate of standing cows by combining the Deeplab V3+semantic segmentation model with the phase-based video magnification algorithm. Biosyst. Eng. 192, 72–89.
Xavier, C., Le Cozler, Y., Depuille, L., Caillot, A., Lebreton, A., Allain, C., Delouard, J., Delattre, L., Luginbuhl, T., Faverdin, P., Fischer, A., 2022. The use of 3-dimensional imaging of Holstein cows to estimate body weight and monitor the composition of body weight change throughout lactation. J. Dairy Sci. 105 (5), 4508–4519.
Xiao, J., Liu, G., Wang, K., Si, Y., 2022. Cow identification in free-stall barns based on an improved Mask R-CNN and an SVM. Comput. Electron. Agric. 194, 106738.
Xiao, J., Si, Y., Xie, M., Liu, G., Yan, Z., Wang, K., 2024. A novel and convenient lying cow identification method based on YOLOX and CowbodyNet: a study with applications in a barn. Comput. Electron. Agric. 225, 109287.
Xu, B., Wang, W., Guo, L., Chen, G., Li, Y., Cao, Z., Wu, S., 2022. CattleFaceNet: a cattle face identification approach based on RetinaFace and ArcFace loss. Comput. Electron. Agric. 193, 106675.
Xu, X., Deng, H., Shang, Y., Wang, Y., Zhang, S., Chen, D., Song, H., 2025a. Multi-camera multi-cow tracking under non-overhead views. Expert Syst. Appl. 291, 128519.
Xu, X., Deng, H., Wang, Y., Zhang, S., Song, H., 2024a. Boosting cattle face recognition under uncontrolled scenes by embedding enhancement and optimization. Appl. Soft Comput. 164, 111951.
Xu, X., Song, H., Pan, H., Chen, D., Yang, S., 2025b. Round-the-clock accurate sheep face recognition via frequency enhancement and cross-modal embedding generation. Comput. Electron. Agric. 239, 110918.
Xu, X., Wang, Y., Shang, Y., Yang, G., Hua, Z., Wang, Z., Song, H., 2025c. Few-shot cow identification via meta-learning. Information Processing in Agriculture. 12 (1), 80–90.
Xu, X., Yang, G., Wang, Y., Shang, Y., Hua, Z., Wang, Z., Song, H., 2024b. Plant leaf disease identification by parameter-efficient transformer with adapter. Eng. Appl. Artif. Intel. 138, 109466.
Xu, Z., Li, Q., Ma, W., Li, M., Morris, D., Ren, Z., Zhao, C., 2025d. A geodesic distance regression-based semantic keypoints detection method for pig point clouds and body size measurement. Comput. Electron. Agric. 234, 110285.
Xu, Z., Zhao, Y., Yin, Z., Yu, Q., 2024c. Optimized BottleNet Transformer model with Graph Sampling and Counterfactual attention for cow individual identification. Comput. Electron. Agric. 218, 108703.
Yamamoto, Y., Akizawa, K., Aou, S., Taniguchi, Y., 2025. Entire-barn dairy cow tracking framework for multi-camera systems. Comput. Electron. Agric. 229, 109668.
Yang, G., Li, R., Zhang, S., Wen, Y., Xu, X., Song, H., 2023. Extracting cow point clouds from multi-view RGB images with an improved YOLACT plus plus instance segmentation. Expert Syst. Appl. 230, 120730.
Yang, G., Qiao, Y., Deng, H., Shi, J., Song, H., 2025. One-stage keypoint detection network for end-to-end cow body measurement. Eng. Appl. Artif. Intel. 146, 110333.
Yang, G., Xu, X., Song, L., Zhang, Q., Duan, Y., Song, H., 2022. Automated measurement of dairy cows body size via 3D point cloud data analysis. Comput. Electron. Agric. 200, 107218.
Yang, L., Xu, X., Zhao, J., Song, H., 2024a. Fusion of RetinaFace and improved FaceNet for individual cow identification in natural scenes. Information Processing in Agriculture. 11 (4), 512–523.
Yang, L., Zhao, J., Ying, X., Lu, C., Zhou, X., Gao, Y., Wang, L., Liu, H., Song, H., 2024b. Utilization of deep learning models to predict calving time in dairy cattle from tail acceleration data. Comput. Electron. Agric. 225, 109253.
Yin, M., Ma, R., Luo, H., Li, J., Zhao, Q., Zhang, M., 2023. Non-contact sensing technology enables precision livestock farming in smart farms. Comput. Electron. Agric. 212, 108171.
Yin, X., Wu, D., Shang, Y., Jiang, B., Song, H., 2020. Using an EfficientNet-LSTM for the recognition of single Cow's motion behaviours in a complicated environment. Comput. Electron. Agric. 177, 105707.
Zeng, F., Li, B., Wang, H., Zhu, J., Jia, N., Zhao, Y., Zhao, W., 2023. Detection of calf abnormal respiratory behavior based on frame difference and improved YOLOv5 method. Comput. Electron, Agric, p. 211.
Zhang, F., Zhou, M., Xiong, B., Yang, Z., Liu, Z., Feng, W., Tang, X., 2024a. Research advances and prospect of intelligent monitoring systems for the physiological indicators of beef cattle. Smart Agriculture. 6 (4), 1–17.
Zhang, H., Zhang, Y., Niu, K., He, Z., 2025a. Neural network-based method for contactless estimation of carcass weight from live beef images. Comput. Electron. Agric. 229, 109830.

Zhang, J., Lei, J., Wu, J., Lu, H., Guo, H., Pezzuolo, A., Kolpakov, V., Ruchay, A., 2023a. Automatic method for quantitatively analyzing the body condition of livestock from 3D shape. Comput. Electron. Agric. 214, 108307.

Zhang, M., Wang, X., Feng, H., Huang, Q., Xiao, X., Zhang, X., 2021. Wearable internet of things enabled precision livestock farming in smart farms: a review of technical solutions for precise perception, biocompatibility, and sustainability monitoring. J. Clean. Prod. 312, 127712.

Zhang, Q., Hou, Z., Huang, L., Wang, F., Meng, H., 2024b. Reparation with moving least squares sampling and extraction of body sizes of beef cattle from unilateral point clouds. Comput. Electron. Agric. 224, 109208.

Zhang, Q., Yang, Y., Liu, G., Ning, Y., Li, J., 2023b. Dairy cow mastitis detection by thermal infrared images based on CLE-UNet. Animals 13 (13), 2211.

Zhang, W., Yang, R., Choi, C., Rong, L., Zhang, G., Wang, K., Wang, X., 2024c. Recent research and development of individual precision cooling systems for dairy cows - a review. Comput. Electron. Agric. 225, 109248.

Zhang, X., Kang, X., Feng, N., Liu, G., 2020. Automatic recognition of dairy cow mastitis from thermal images by a deep learning detector. Comput. Electron. Agric. 178, 105754.

Zhang, Y., Zhang, Y., Ga, M., Wan, X., Dai, B., Shen, W., 2025b. Multimodal behavior recognition for dairy cow digital twin construction under incomplete modalities: a modality mapping completion network approach. Artif. Intell. Agric. 15 (3), 459–469.

Zhao, J., Lian, Q., 2022. Compact loss for visual identification of cattle in the wild. Comput. Electron. Agric. 195, 106784.

Zhao, K., Duan, Y., Chen, J., Li, Q., Hong, X., Zhang, R., Wang, M., 2023a. Detection of respiratory rate of dairy cows based on infrared thermography and deep learning. Agriculture 13 (10), 1939.

Zhao, K., Jin, X., Ji, J., Wang, J., Ma, H., Zhu, X., 2019. Individual identification of Holstein dairy cows based on detecting and matching feature points in body images. Biosyst. Eng. 181, 128–139.

Zhao, K., Zhang, M., Ji, J., Zhang, R., Bewley, J., 2023b. Automatic lameness scoring of dairy cows based on the analysis of head- and back-hoof linkage features using machine learning methods. Biosyst. Eng. 230, 424–441.

Zhao, K., Zhang, M., Shen, W., Liu, X., Ji, J., Dai, B., Zhang, R., 2023c. Automatic body condition scoring for dairy cows based on efficient net and convex hull features of point clouds. Comput. Electron. Agric. 205, 107588.

Zhao, W., Yang, X., Lyu, Z., Xu, C., Guan, Z., 2025. Road of large language model: source, challenge, and future perspectives. Research 8, 0655.

Zheng, Z., Qin, L., 2023. PrunedYOLO-Tracker: an efficient multi-cows basic behavior recognition and tracking technique. Comput. Electron. Agric. 213, 108172.

Zheng, Z., Zhang, X., Qin, L., Yue, S., Zeng, P., 2023. Cows' legs tracking and lameness detection in dairy cattle using video analysis and Siamese neural networks. Comput. Electron. Agric. 205, 107618.

Zhou, G., Ye, W., Li, S., Wang, Z., Li, G., Li, J., 2025. FGPointKAN++ point cloud segmentation and adaptive key cutting plane recognition for cow body size measurement. Artif. Intell. Agric. 15 (4), 783–801.

Zhou, M., Zhou, S., Xiong, B., Li, Z., Condotta, I., Dilger, R., Li, J., Tang, X., 2026. Humanoid animal behavior labeler: an interactive annotation agent to accelerate ethological applications in precision management of animals using large vision-language models. Comput. Electron. Agric. 241, 111307.