

Digital Technologies for Cattle: A Review of Automated Welfare-Related Monitoring Systems in Smart Farms

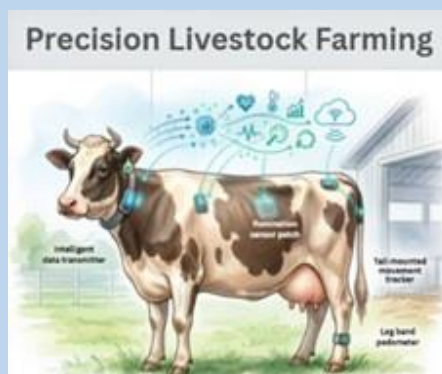
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Abstract: Objective: As the global livestock sector shifts from periodic manual inspections toward continuous objective assessments, it is undergoing a digital transformation driven by Precision Livestock Farming (PLF). This review aims to evaluate automated monitoring systems for beef and dairy cattle welfare.

Methods: This review synthesizes evidence from 118 publications, identified through a systematic search of five major databases. We critically assess two primary technological categories: non-contact computer vision systems and wearable Internet of Things (IoT) infrastructures. The computational evolution driving these tools is also evaluated, mapping the transition from traditional statistical methods to advanced deep learning architectures, such as YOLO variants and Vision Transformers (ViTs). **Key Findings:** Current evidence demonstrates that these systems can effectively monitor ingestive dynamics, detect early locomotion anomalies, and assess micro-environmental comfort. However, a principal limitation in the existing literature is the frequent lack of rigorous external validation across heterogeneous commercial farms, which complicates the translation of high algorithmic accuracy into robust biological validity. **Conclusions:** While these technologies hold significant potential to improve cattle welfare, they also introduce socio-technical risks, including data objectification and reliance on unvalidated alerts. **Recommendations:** This review highlights the critical need for standardized validation protocols and discusses Generative AI (GenAI) and Large Language Models (LLMs) strictly as emerging, prospective research directions rather than currently established PLF solutions.



Keywords: precision livestock farming, cattle welfare, computer vision, Internet of Things, automated behavior monitoring, deep learning.

Introduction

In the last few decades, the world's livestock industry has experienced a revolution in response to increased economic pressures, larger numbers of animals kept and the very real necessity for sustainable food production systems which incorporate farm engineering and animal welfare [1-4]. The contribution of Precision Livestock Farming (PLF) to sustainable cattle production should be evaluated within a multidimensional framework integrating environmental performance, animal health and welfare, resource efficiency, and socio-economic viability, rather than considering technological efficiency as an isolated sustainability outcome [5].

In traditional animal husbandry, the experience of the animal caretaker, and occasional sightings, have been relied upon. As modern commercial business grows, however, the ratio between animals and humans becomes much larger, and manual inspection becomes more difficult, inefficient, and inaccurate [6, 7]. To overcome this ever-increasing operational difference, the concept of PLF has been found to be a key component in smart farming [8]. PLF should be conceptualized at the system level rather than as the simple deployment of individual sensors, requiring integration between data acquisition, data management, algorithmic interpretation, decision support, and subsequent management actions [9]. Using advanced digital

infrastructures, PLF aims to provide real-time, non-invasive and continuous monitoring of livestock, changing the paradigm of livestock management from reactive to automated, data-driven and highly personalized care of individual animals [6].

At the same time, animal welfare is not only measured as survival and health but also as an integral concept, which considers the positive emotional state and behavioral freedom of the animals [10, 11]. On-farm welfare auditing traditionally has been based on many standardized manual assessment protocols, one of which is the Welfare Quality® framework [12]. Although these protocols establish crucial baseline measurements, including indicators related to animals, resources, and management, their application is limited by their intermittent nature, often providing only a real-time assessment of the herd [13, 14]. While continuous automated sensing significantly improves temporal accuracy, it does not automatically measure animal welfare more accurately than properly conducted animal-based manual assessments; therefore, digital monitoring and approved animal welfare protocols should be viewed as complementary approaches. Moreover, manual scoring for more complex diseases like lameness or respiratory affections is physically taxing and has high inter-observer variability [15]. These problems can be

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solved by the digital transition in smart farms, which introduces automatic monitoring systems that record high-frequency behavioral and physiological characteristics [8, 13]. Modern PLF schemes introduce continuous sensory monitoring systems that allow the setting of individual animal baseline ranges, which can support the identification of subclinical abnormalities. However, continuous data acquisition should not be automatically equated with clinically useful early detection, as true detection capability depends strongly on sensor sensitivity, specificity, reference standards, validation populations, and appropriately calibrated alert thresholds [16, 17].

The social and economic and ethical dimensions of the widespread uptake of digital technologies in animal production systems are complex [12]. Another important socio-economic benefit of automated monitoring is the efficient use of resources, animal health protection and reduction of physical strain on farmers [6, 8]. The sustainability value of precision monitoring may also arise indirectly through improved biological resilience, since earlier identification of health and reproductive problems can support longevity, reduce involuntary replacement, and improve lifetime resource efficiency [5]. On the theoretical side, the fusion of high-dimensional sensor data enables the development of "digital representations" in the form of virtual profiles that combine the animal's physiological and behavioral data, thus reintroducing the animal to the manager's focus in large-scale production systems, on a much more precise level than ever before [8]. At the same time, this digital revolution raises very deep ethical and socio-technical issues [12]. Although the use of PLF systems has been embraced, there are inherent risks associated with their deployment. These include "automated alienation," which manifests as a physical and emotional disconnection between farmers and animals due to reliance on remote interfaces, and "data objectification," where sentient animals are reduced to mere data points and production metrics. Additionally, there is a significant risk of depending upon inaccurate or unvalidated sensor warnings [11, 18]. Therefore, a holistic view of the technological capabilities of these systems is necessary, considering the ethical implications to make sure that digital technologies improve the wellbeing of the animals as a whole [18, 19].

To provide a rigorous and reproducible synthesis of current automated monitoring systems in smart beef and dairy farms, a systematic literature search was conducted. The search targeted five major scientific databases: Scopus, Web of Science, ScienceDirect, IEEE Xplore, and PubMed, focusing on peer-reviewed journal articles and conference proceedings published in English between 2015 and early 2026. The primary Boolean search string utilized was:

(cow OR bovine) AND ("precision livestock farming" OR "smart farm" OR "digital technolog" OR "computer vision" OR "machine learning" OR "artificial intelligence" OR "sensor") AND (welfare OR behavior*)*

To ensure comprehensive coverage of the diverse applications discussed in this review, the primary search was supplemented with targeted secondary queries using specific terms such as "lameness detection," "respiratory disease," "biometric identification," and "precision slaughter."

Studies were included if they met the following criteria: (1) focused on cattle (dairy or beef); (2) evaluated the application of PLF technologies, computer vision, wearable sensors, or AI algorithms; and (3) assessed outcomes directly related to animal welfare, health monitoring, or behavioral analytics. Conversely, studies were excluded if they: (1) focused solely on clinical, nutritional, or genetic aspects without a digital monitoring

component; (2) involved non-bovine species; or (3) lacked sufficient technical or algorithmic validation.

The initial database search yielded 139 articles after the removal of duplicates. During the first screening phase based on titles, 16 articles were excluded due to irrelevance to the target scope, leaving 123 articles. A subsequent evaluation of the abstracts led to the exclusion of 13 additional articles that lacked a clear technological or AI focus, reducing the pool to 110. Full-text analysis of the remaining articles resulted in the exclusion of 8 papers due to insufficient methodological detail, yielding a core matrix of 102 studies. To further strengthen specific technological and biological contexts (e.g., multimodal data fusion, LLMs, and environmental sustainability tradeoffs), an additional targeted search was performed, resulting in the inclusion of 16 recent, highly relevant studies. Consequently, the final review synthesizes 118 authoritative references. The complete study selection process, detailing the sequential screening phases and the application of inclusion and exclusion criteria, is visually summarized in the literature selection flowchart (Figure 1).

For the finalized reference matrix, key variables were systematically extracted to facilitate comparative analysis. These variables included the target physiological or behavioral parameter, sensor technology deployed, specific AI/ML architecture (e.g., YOLO variants, ViTs), dataset size, validation approach, and principal performance metrics, which are synthesized in the respective tables.

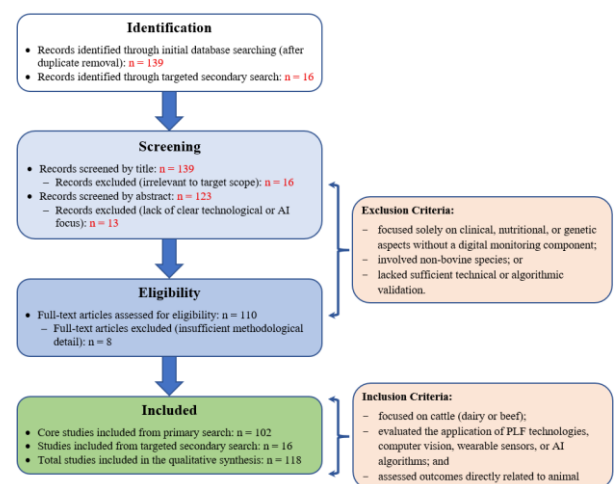


Figure (1): Flowchart illustrates the systematic literature search, screening, and selection process for the reviewed studies.

Technological Frameworks for Automated Data Acquisition

The realization of automated welfare monitoring in smart farms necessitates robust technological frameworks capable of continuous, high-frequency, and reliable data collection. This section delineates the primary sensory modalities and physical architectures leveraged for automated data acquisition, systematically categorizing them into non-contact optical network systems and wearable bio-logging Internet of Things (IoT) infrastructures, as comprehensively illustrated in Figure 2.

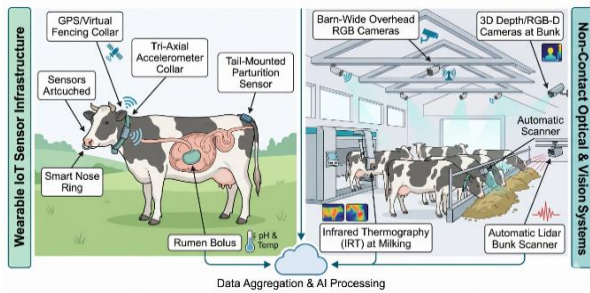


Figure (2): Comprehensive architectural taxonomy of automated data acquisition frameworks in smart cattle farming, distinguishing between wearable IoT sensor infrastructures and non-contact optical and computer vision systems.

Non-Contact Optical and Computer Vision Systems

Despite their advantages, the commercial readiness of computer vision systems heavily depends on overcoming practical limitations such as optimal camera geometry, high stocking densities, severe occlusion, variable illumination, specific breed and coat characteristics, the quality of manual data annotation, and the critical challenge of domain shift between different farm environments. However, in the field of PLF, non-contact monitoring paradigms have proved to be very popular because they involve none of the physical handling and discomfort of the animals. These optical structures can use a variety of imaging sensors to capture high resolution spatial, physiological and morphological properties, ranging from structural dimensions to thermal and volumetric properties, as described below [20, 21].

Red-Green-Blue Surveillance and Multi-Camera Network

Architectures: The most widely used sensing infrastructure in current environments of PLF are the standard Red-Green-Blue (RGB) surveillance systems which enable continuous monitoring of animal behavior without the stress or physical discomfort caused by manual observations. Recent studies indicate that there is a clear move toward barn-wide and entire-barn tracking systems using multi-camera networks which are made up of multiple cameras with overlapping fields of view [22, 23]. Additionally, low-cost 360-degree fisheye cameras have shown to be sufficient for high capture rates to monitor both daily behavioral time budgets and may be limited in low-light situations [24]. Such distributed network architectures are essential to handle extreme herd densities and barn interior geography that creates temporary tracking loss and severe occlusion [22, 25]. These vision systems seamlessly combine overhead camera views with automated classification algorithms to continuously estimate daily activity budgets, herd spatial distribution, traffic flow patterns and non-invasively extract key physiology metrics like respiration rates directly from raw video streams [26-28].

Three-Dimensional Depth Sensing: RGB-D and Time-of-Flight Sensors

Three-dimensional computer vision offers a powerful spatial modality that is useful in many ways to deal with the traditional 2D imaging limitations like variability in light conditions, shadow, and low contrast farm environments. [29]. Low-cost Time-of-Flight (ToF) and depth-sensing arrays (such as the Microsoft Kinect) are able to produce high fidelity dorsal and lateral point clouds, which can be used to automatically estimate skeletal traits including wither height, hip height, chest girth and to achieve precise liveweight predictions, without requiring contact [29, 30]. The overhead RGB-D camera configurations enable an enhancement to the group-housing system by allowing the measurement of the individual feed intake at the feed bunk, an important health and welfare indicator that was not possible to measure in commercial housing system [31]. In addition, deep learning pipelines based on depth data can be

used to perform high throughput phenotyping of udder and teat conformation in Automated Milking Systems (AMS) [32]. In the field of locomotion analysis, algorithms for 3D pose estimation have been developed to track anatomical landmarks during posture changes (such as a sequence of lying and standing) and to provide objective and quantified measures of cubicle comfort for freestalls and other forms of physical stress [20, 33-35].

Infrared Thermography and Dual-Spectrum Imaging:

Infrared thermography (IRT) is a highly effective diagnostic tool used for non-contact physiological monitoring which can detect the surface thermal changes associated with underlying metabolic or pathological conditions [36]. The major use of automated IRT is the early detection of subclinical and clinical mastitis, localized inflammatory areas are identified by the differences in temperature between the quarters or by comparison to individual historical basis [37]. The state of the art is dual-spectrum (RGB-Thermal) data fusion models [38, 39] since all the above-mentioned environmental variables, which can influence raw thermal tracking, are confounding. The combination of optical matrices and thermal matrices significantly improves regional segmentation accuracy, enabling automatic scoring of the cleanliness of animals [38] and continuous assessment of stress responses in pre-slaughter handling and crowding conditions [39].

Specialized Multi-View Stereo Vision and Laser/Lidar

Scanners: The multi-view stereo vision architectures take advantage of multi-angle camera synchronized setups to perform a robust 3D structural reconstruction of cattle using statistical and guided filtering techniques to suppress noise in the point cloud due to the reflectivity of the cattle's fur and/or complex lighting conditions [40]. Laser and lidar technologies have also evolved to precision feeding operations, especially in intensive beef feedlots. In parallel, the automated bunk lidar system generates data on the level and distribution of feed dry matter down the bunk, from which feed allocation algorithms optimize growth and physiological health and protect animal welfare by measuring the feed level [41, 42]. Moreover, non-optical methods based on ultrasonic distance sensing and Support Vector Machines (SVM) have shown to be promising methods for position and spatial location tracking in complex environments [43].

Wearable Sensors and IoT Infrastructure

Computer vision can provide full-scale information on the environment and the groups, whereas wearable bio-logging devices and connected IoT infrastructures can give granular information that allows for continuous individual-level physiological and behavioral budgeting. This distributed sensor system is the base system for constant individual surveillance in both intensive indoor barns and extensive pasture systems. These IoT data communication gateways enable the flow of real-time data, making it possible to respond quickly to alerts around welfare issues while using resources efficiently [44]. However, evaluating the commercial readiness of these infrastructures requires acknowledging several practical limitations. Beyond battery life and hardware deterioration, wearable performance is significantly affected by attachment position, sensor displacement over time, suboptimal sampling frequencies, calibration issues, missing data, individual biological variability, and potential device-related behavioral effects [45].

Accelerometers: Collars, Tail-Mounted Devices and

Nose Rings: Both intensive and extensive farming systems use bio-logging technology for wearable individuals, continuous behavioral budgeting (i.e., attaching sensors directly to animals to record physiological and behavioral data). Raw g-forces are collected by tri-axial accelerometers placed inside collars on the

neck and are mapped to core behaviors that occur during the day, such as lying, standing, feeding, and rumination duration [46, 47]. For increased granularity of ingestive behavior tracking, advanced configurations have been developed using wearables nose ring sensors; these devices measure accelerations vectors at high frequency directly linked to jaw motions, resulting in greater accuracy in discriminating bite, chew and chew-bite sequences [48]. In the realm of reproductive and life cycle monitoring, tail-mounted accelerometer sensors monitor the dynamics of tail motion, capturing subtle variations in the amplitude and frequency of the motion, and making very accurate predictions of calving onset and parturition timing, as well as heat detection [49]. Despite their widespread adoption, current smart collars still face important limitations related to multisensor integration, interoperability, energy autonomy, economic accessibility, and the conversion of continuously collected data into actionable information for farmers [50].

Radio Frequency Identification and Indoor Ultra-Wideband Localization Systems: The history of the individual animal tracing, electronic data logging, and automated drafting for precision dairies is based on Radio Frequency Identification (RFID) networks [16, 22]. Most of the current smart farms are moving toward the use of indoor Ultra-Wideband (UWB) localization architectures, however, since existing RFID architectures record only short-range interactions at specific locations (e.g., a feeder or a milking stall). To overcome this, the adoption of indoor UWB localization architectures is a new approach. UWB architectures are able to deliver multiple cows simultaneously, both in terms of time and space, with high precision in free stall environments. The combination of these continuous spatial localization tracks with high frequency behavioral data collected from wearable accelerometers greatly lowers the amount of classification errors, allowing for accurate detection of social interaction, resource visits, and early detection of locomotor anomalies [51].

Rumen Boluses and Smart Water Point Electronic Loggers: While the initial administration of in-dwelling telemetric devices (e.g., rumen boluses) is physically invasive, once placed, they provide continuous physiological monitoring without repeated handling, offering insight into the internal core temperature and pH and allowing individual normal ranges to be established, which can also be used for pre-symptomatic diagnosis of metabolic disorders and acute systemic inflammation [15]. An automated electronic drinker with a constant-level sensor, inline flow sensor, and RFID antenna allows for individual herd drinking kinetics and resource attendance to be tracked at the herd level [52, 53]. These smart water point loggers can automatically determine agonistic replacements and dominance hierarchies during periods of high demand [52]. In addition, water intake is very sensitive to

physical stress, making it a good non-invasive early warning for Bovine Respiratory Disease (BRD) and infectious affections during critical adaptation periods [54].

Remote Spatial Tracking Networks: LP-GPS, GIS, and Satellite/SigFox Protocols: Manual management of the herd is challenging because of the large reach of the land, while extensive grazing and pasture production systems call for long range and energy resilient spatial monitoring systems [19, 55]. Global Positioning System (GPS) collars can be used to trace long-term itineraries of grazing and resource utilization, but the accuracy of distance measurement is still critically dependent on optimal sampling frequency to prevent erroneous distances from meandering animal movements [56]. Today, IoT applications combine low power GPS bands (LP-GPS) with long-range wide-area network (LRWAN) protocols, such as Sigfox, to achieve greatly extended battery life for devices [57]. The spatial datasets are then analyzed using Geographical Information Systems (GIS) and algorithms such as Kernel Density Estimation (KDE) to produce dynamic representations of heat maps that show behavioral patterns and the identification of pasture utilization hotspots [57]. Virtual fencing (VF) technologies are a remote spatial infrastructure that are used to control cattle distribution and exclude herds from environmentally sensitive areas via automated neckbands that provide conditional audio warnings and electric pulses based on real-time GPS boundary logic [58, 59].

Bioacoustic Monitoring and Low-Power Audio Circuit Architectures

Bioacoustic monitoring is an important auditory component of automated welfare monitoring based on continuous signal processing, which captures and interprets the sound waves produced by the livestock or their macro-environment. Ingestive sounds are captured by high-resolution acoustic circuits and specialized microphones set up in grazing or indoor environments, with noise-robust algorithms that are able to detect specific foraging events (bites and chews) from high noise levels such as machine or herd movement [60]. These acoustic architectures are designed to be on-chip processed by low-power microcontrollers (such as ARM Cortex backbones), allowing on-line, continuous analysis of vocalization [61]. Through deep learning analysis of spectral characteristics of vocalizations (e.g., mel-spectrograms), bioacoustic systems can automatically categorize sounds into different categories of animal behavior and emotion (e.g., distress, hunger, estrus) and translate the raw vocal signs of poor welfare into decision-support alerts for farm operators [61, 62].

Table (1) summarizes the target parameters, practical strengths, and distinct operational limitations of all discussed optical, wearable, and bioacoustic modalities.

Table (1): Comparative overview matrix of optical, wearable, and bioacoustic data acquisition modalities in cattle welfare monitoring.

Data Acquisition Modality	Target Welfare & Physiological Parameters	Practical Strengths (Welfare & Operations)	Operational Constraints & Limitations	Key References
RGB Surveillance & Multi-Camera Networks	Daily activity budgets, spatial distribution, respiratory rates, feeding duration.	Non-invasive barn-wide tracking; eliminates physical handling stress; 360-degree cameras offer cost-effective high capture rates.	Vulnerable to severe occlusions, temporary tracking loss in dense herds, and low-light conditions.	[22-28]
3D Depth / ToF Sensors	Skeletal traits, liveweight prediction, feed intake, posture transitions (cubicle comfort).	Overcomes 2D lighting/shadow limitations; accurately extracts structural morphology and spatial depth.	Susceptible to direct sunlight in open sheds and rapid animal movements; requires precise angular calibration.	[20, 29-35]
IRT	Subclinical mastitis detection, animal cleanliness scoring, pre-slaughter stress responses.	Provides direct, non-contact physiological and inflammatory insights through surface thermal mapping.	Highly sensitive to confounding environmental variables (wind speed, ambient humidity, dirt).	[36-39]

Data Acquisition Modality	Target Welfare & Physiological Parameters	Practical Strengths (Welfare & Operations)	Operational Constraints & Limitations	Key References
Laser / Lidar Scanners	Feed bunk management, feed dry matter volume, spatial location tracking.	Robust structural reconstruction; unaffected by lighting; optimizes feed allocation efficiently.	Specific physical setups required; point cloud noise generated by fur reflectivity.	[40-43]
Wearable Accelerometers (Collar, Nose, Tail)	Ingestive behavior (bite/chew), calving onset, rumination, lying/standing budgets.	Delivers continuous, individualized, and high-frequency behavioral data with high granularity.	Potential data drift if unvalidated; hardware wear and tear; battery life limits; physical stress of wearing tags.	[45-49]
RFID & Indoor UWB	Individual tracing, resource visits, dominance hierarchies, high-precision spatial tracking.	UWB provides continuous high-precision indoor tracking; RFID ensures reliable identification.	RFID only logs punctual, short-range interactions; UWB requires dense indoor antenna infrastructure.	[16, 22, 51]
Rumen Boluses & Smart Drinkers	Internal core temperature, pH, drinking kinetics, BRD early warning.	Highly sensitive to physiological stress; provides unobtrusive insight into internal metabolic states.	Boluses require invasive administration; smart drinkers need constant calibration for flow sensors.	[13, 52-54]
Bioacoustic Microphones	Foraging events (bites/chews), vocalizations (distress, hunger, estrus).	Effective in low-visibility environments; captures direct emotional and physiological cues.	Severe background interference (e.g., machinery, herd movement) requires complex filtering algorithms.	[60-62]
Remote Spatial Tracking (LP-GPS & Virtual Fencing)	Rangeland utilization (KDE heatmaps), boundary enforcement, dynamic pasture management.	Operates over vast geographic scales; excludes herds from sensitive zones without physical fences.	Battery longevity constraints; short sampling intervals overestimate distance due to GPS error accumulation.	[55-59]

Abbreviations: 3D, three-dimensional; BRD, bovine respiratory disease; GPS, Global Positioning System; IRT, infrared thermography; KDE, kernel density estimation; LP-GPS, low-power Global Positioning System; RFID, radio frequency identification; RGB, red-green-blue; ToF, time-of-flight; UWB, ultra-wideband.

Artificial Intelligence Algorithms and Computer Vision Models in PLF

A major part of the successful use of PLF is the ability to process the large, high dimensional amounts of data available, as well as the sensory hardware. It is crucial to note that successive YOLO version numbers do not represent a straightforward evolutionary scale of biological validity.

Over the last several years, the approach that shifted from a traditional statistical model to sophisticated Artificial Intelligence (AI) and deep learning architecture has allowed real-time, automated decision making in complex farm settings. The comprehensive computational workflow and algorithmic pipeline for processing these heterogeneous data streams are systematically diagrammed in Figure 3.

Deep Learning Object Detection and Instance Segmentation Network Backbones

Accurate detection, localization and segmentation of individual animals or specific anatomical areas within the visual frame is the core of the baseline architecture of any computer vision system in precision livestock management. This subsection covers the advancement of deep learning object detection networks and pixel-level semantic segmentation backbones, and their essential functions in laying the groundwork for spatial sensing that's vital for automated cattle monitoring and localized behavioral analysis.

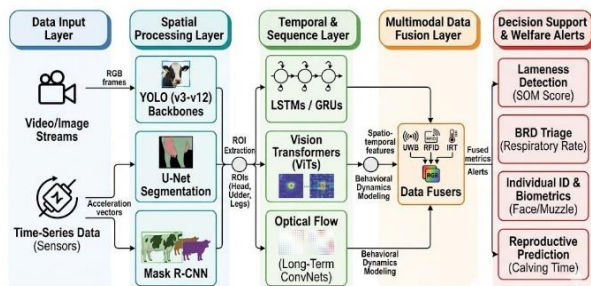


Figure (3): Algorithmic processing pipeline showing the end-to-end flow of heterogeneous data modalities through spatial and temporal deep learning frameworks to generate actionable cattle welfare decision-support alerts.

Development and Application of You Only Look Once (YOLO) Architectures:

Object detection is a key preliminary task in computer vision that is essential for the subsequent analyses of localized behavior and individual animal tracking. YOLO (You Only Look Once) family of single-stage object detectors have become a widely adopted standard in PLF due to their effective trade-off between accuracy and real-time inference speed [64]. The literature shows that the YOLO architecture has been continuously evolving to address problems encountered in agriculture. For example, the Region of Interest (ROI) can be defined as the top of the cow's head for non-invasive identification as in [65] and the body parts for automating locomotion scoring for lameness detection as in [66] have been widely used with YOLOv3 and YOLOv5. Furthermore, better YOLOv5 models have been able to provide the solution to distinguish single beef cattle in an overlapping crowd [67].

YOLOv7 was then applied to body key point recognition for highly accurate body key point measurements, which helped with non-contact 3D body measurements [40]. State of the art models have been compared for fine grained feeding activity detection in recent years, such as YOLOv8m [64] and YOLOv10m, which have shown to have high precision, but with slightly better consistency in training, while YOLOv8 is the fastest to reach the optimal training stage. In a recent thorough analysis of newer architectures (YOLOv9 - YOLOv12) for numerical label detection under severe occlusions, it was found that YOLOv12m provides a higher detection accuracy whereas for edge deployment, YOLOv11m is a better choice for a balance between accuracy and computational cost [63]. Considering the requirement to handle the harsh outdoor environment, computational constraints of the edge devices, and varying weather conditions in the outdoor scenes, lightweight versions, like CBR-YOLO (based on YOLOv8), have been developed to retain the ability to recognize a scene even under multiple weather conditions in outdoor scenes [68]. Furthermore, the YOLOX framework and variants (e.g., YOLOX-s) have been shown to demonstrate competitive performance compared to other algorithms for specific breed identification (e.g., Holsteins) using complex coat patterns [69] and for mechanical brush use for welfare assessment [70]. To contextualize the reported efficacy of these diverse architectures, Table (2) summarizes the specific variants deployed, their functional targets, and their reported performance metrics alongside crucial methodological

characteristics. Because performance metrics are highly dependent on heterogeneous dataset sizes, environmental conditions, and validation approaches (e.g., random frame splits versus strict temporal or cow-level separation), direct cross-study comparisons of algorithmic superiority should be interpreted with caution. Consequently, Table (2) details the specific validation strategies employed in each study to provide a transparent framework for evaluating algorithmic robustness in real-world PLF applications.

Semantic Segmentation Networks and Convolutional Architectures: In addition to bounding-box object detection, semantic and instance segmentation networks play a crucial role in the morphological analysis of the animal at the pixel level. For instance, U-Net semantic segmentation algorithms can automatically identify wounds/lesions in video data, with high accuracy, and solve the challenge of scoring a hock wound with manual methods, which are highly variable [71]. These complex tasks are supported by Deep Convolutional Neural Networks (CNNs). An application of CNNs that has been successfully applied for automated physical conformation scoring is for the semantic segmentation and key point detection of complex anatomical milking system traits in depth images, which is known as AMS [32]. Furthermore, AMS should be considered integrated biological and technological platforms since their welfare benefits depend not only on sensor availability but also on the alignment of automation with mammary physiology, cow traffic, teat tissue integrity, and management practices [72]. For applications where a degree of millimeter accuracy is required, such as digital dermatitis detection or early diagnosis of lameness [66, 73] these segmentation frameworks can be employed to precisely extract the target features from cluttered backgrounds.

Advanced Sequence Modeling, Attention Mechanisms, and Trajectory Tracking

Spatial localization gives a snapshot of what an animal is doing at one frame, but to understand the complex behaviors and subtle health changes that exist over time will need to capture the continuous temporal dynamics of both high-frequency sensor data and video sequences. The advanced sequence modeling architectures, Vision Transformers (ViTs) and multi-object tracking frameworks optimized to preserve the continuity of individual identities and model long-term behavioral patterns in dynamic herd environments are explored.

ViTs and Self-Attention Encoders: Spatial feature extraction has been a hallmark of computer vision for many years with the CNNs, but the latest trend in PLF is the ViTs and the attention mechanisms, which excel at encoding the global context of an image. Attention mechanisms enable models to attend to key parts of the frame rather than processing individual pixels one by one. The accuracy of liveweight estimation was greatly enhanced by attention layers in the Spatial and Channel Attention Convolution Network (SCA-ConvNet), which were able to combine physical measurement parameters with images effectively [74].

In behavioral and health analytics, the end-to-end Transformer model (VideoMAE) has revolutionized respiratory rate monitoring by predicting breathing patterns directly from RGB videos, completely bypassing the error-prone intermediate steps of ROI tracking [26]. Furthermore, Vision Transformer-based architectures, incorporating Swin Transformer backbones and deformable attention encoders, have successfully automated the visual health scoring of calves, focusing on critical phenotypic indicators of BRD such as ocular discharge and ear posture [75].

Recurrent Architectures and Time-Series Analytics: Physiological and behavioral data collected from wearables (such as accelerometers, rumen bolus etc.) should be modeled as being temporally dependent. Random Forest and Gradient-Boosted Trees (XGBoost) are examples of machine learning algorithms that have been effectively applied to the aggregation of daily behavioral patterns into complete welfare indices and the classification of behavioral pathologies such as metabolic disorders and estrus [14, 17]. Wearable nose-ring accelerometer data has been used with advanced classifiers and Long Short-Term Memory (LSTM) networks to discriminate complex ingestive behaviors, such as rumination and feeding, for high-frequency motion data [48]. Single-stream long-term optical flow convolution networks (LT-CN) are state-of-the-art methods for early diagnosis of lameness using vision-based temporal analysis that enable the extraction of the full spatio-temporal dynamics of the walking posture over a few seconds [76].

A critical methodological concern in these longitudinal animal datasets is the risk of data leakage. Random splitting at the frame or observation level can inadvertently place measurements from the same animal in both the training and testing sets, thereby substantially inflating apparent model performance. Consequently, strict animal-level, farm-level, and ideally, external domain validation must be considered as central requirements for robust PLF model evaluation [8].

Multi-Object Tracking Algorithms and Spatial Interaction: Target occlusion and ID switching, where the tracking system loses an animal and mistakenly assigns its ID to another, are severe challenges in dense herds that must be overcome for continuous individual monitoring [18]. Multi-object tracking (MOT) frameworks have been developed and improved to keep individual objects alive over time. The YOLO-BoT algorithm, which combines YOLOv8s with the tracking logic BoT-SORT and the self-attention technique, has been effectively able to track the cattle behaviors and prevent the occlusion problem in severe cases, with the result of tracking the behaviors with a reported accuracy of nearly 100% within its specific experimental dataset [31]. However, novel location-based projection algorithms and Vision Transformer based multi-camera tracking frameworks are deployed to extend the tracking over the whole barn. These systems provide good continuity of identity through the fields of view of multiple cameras despite cows moving across the field of view of two or more cameras, which may be distorted by the lens [23, 77].

Table (2): Summary of methodological characteristics and reported performance of YOLO and Vision Transformer (ViT) architectures applied in cattle monitoring systems.

Specific Variant Deployed	Functional Target / Animal Region	Dataset Size (Animals)	Validation Approach	Principal Performance Metric	Key Finding & Application	Citations
CNN / YOLO-based	Non-invasive ID (Top of head) & feeding behaviour	7,265 images (17 Holstein cows)	Temporal split (training/testing on different days)	Accuracy: 97.06%	Effective for initial ROI isolation for non-invasive ID and tracking.	[65]

Specific Variant Deployed	Functional Target / Animal Region	Dataset Size (Animals)	Validation Approach	Principal Performance Metric	Key Finding & Application	Citations
Improved YOLOv5	Group beef cattle ID (Dorsal/back patterns)	2,397 images (95 beef cattle)	8:2 random split	Precision: 93.2%; mAP: 97.6%	Distinguishes single beef cattle in an overlapping crowd with high precision.	[67]
YOLOv7	3D body measurements (Body keypoints)	47 dairy cows & 1 model cow	On-farm real-world validation vs. manual measurements	Average relative error: 1.74%	Enabled highly accurate anatomical keypoint recognition, facilitating 3D measurements.	[40]
YOLOv8m & YOLOv10m	Feeding activities (biting, chewing, visiting)	1,200 frames (12 Charolais bulls)	70:10:20 strict video-level separation	YOLOv10m mAP: 94.0%; YOLOv8m mAP: 92.0%	Achieves optimal training quickly for fine-grained feeding activity detection.	[64]
CBR-YOLO (YOLOv8)	Behavior recognition (General scene)	5,051 augmented images (Multiple cattle)	8:1:1 random split	mAP@0.5: 90.2%; Precision: 90.7%	Lightweight variants maintain robustness under harsh, multi-scene weather conditions.	[68]
YOLOv11m & YOLOv12m	Numerical labels ID under severe occlusions	91,694 annotated frames (90 dairy cows)	Train/val split over multi-camera system	YOLOv12m mAP50: 94.7%; mAP50-95: 91.1%	YOLOv12m yields highly effective accuracy for numerical label detection.	[63]
YOLOX-S-TKECB	Breed-specific ID (Complex coat patterns)	61,663 augmented images (150 Holstein cows)	Train/test split	mAP: 97.87%	Outperforms standard algorithms in breed-specific identification using coat patterns.	[69]
YOLOX & HRNet	Mechanical brush use patterns (Body posture)	1.77 million frames (50 cows)	70:30 strict temporal split	Macro-average accuracy: 88%	Effectively assesses mechanical brush use for welfare monitoring.	[70]
Multi-camera tracking	Entire-barn spatial tracking	58 min video (43 cows)	Temporal bootstrapping (5 segments)	MOTA: 86.5%; IDF1: 81.4%	Enables robust multi-camera tracking with good continuity of identity across the barn.	[23]
VideoMAE (ViT)	Respiratory rate (Thoracic region)	807,000 frames (6 dairy cows)	Strict cow-level split (leave-one-out)	MAE: 2.58 bpm; RMSPE: 15.03%	Predicts respiratory rates directly from RGB video bypassing ROI tracking.	[26]
Swin Transformer & Deformable Encoder	Automated calf respiratory health scoring (Ocular, nasal, ear posture)	5,374 annotated frames (100 Holstein calves)	Field-collected video frames validated against consensus of 3 trained expert annotators	Nasal F1: 0.88; Ocular F1: 0.86; Ear F1: 0.82	Model adaptively attends to fine-grained, localized clinical signs handling subtle symptom variations.	[75]
YOLO11m & SAMURAI (SAM 2.1)	Multi-camera multi-object tracking (Entire barn panoramic view)	2,129 train/val images & 3 test videos (35 cows)	81:10:9 split (independent test set with no temporal overlap)	MOTA: 99.3%; IDF1: 99.7%; YOLO11m mAP: 0.97	Geometrically aligns camera feeds to eliminate redundant detections and cross-camera identity switches.	[77]

Abbreviations: mAP, mean average precision; IoU, intersection over union; MOTA, multiple object tracking accuracy; IDF1, identification F1 score; MAE, mean absolute error; RMSPE, root mean square percentage error; bpm, breaths per minute; ROI, region of interest.

Multimodal Machine Learning and Heterogeneous Sensor Data Fusion Architectures

Animal welfare is multi-dimensional, and no single sensor can measure the whole. So, modern PLF systems are transitioning toward multi-modal machine learning and data fusion systems. Data from different data sources can be fused together, for example using the high precision spatial location data from UWB indoor systems with movement data collected from a wearable accelerometer in order to make the classification of complex behaviors much more accurate than unimodal approaches [51]. This has been shown to be effective for combining visual facial expressions (DenseNet-121) with locomotion accelerometer data (LSTM and multi-head attention) and improve the early detection of lameness by a substantial margin compared to single modality systems [78]. Likewise, the Group Sparse Representation based Classification (GSRC) algorithm considers biometric identification as a multimodal biometric problem, combining high-dimensional texture descriptors, and offering highly accurate identification accuracy, without requiring the traditional tagging procedure which would otherwise be invasive [79]. On the herd management level, the combination of IoT edge processing with the integration of barn

environmental sensor data (temperature, humidity etc.) and individual cow behavioral data, can enable the real-time holistic modelling of welfare and accurate prediction of heat stress [47, 80]. The value of such automated systems may extend beyond biological monitoring, since routinely generated AMS records can be integrated with nutritional and economic information to evaluate management strategies and support technical-economic decision-making under commercial conditions [81].

When integrating these heterogeneous sources, architectures typically employ early fusion (combining raw data), intermediate/feature-level fusion (combining extracted features), or late/decision-level fusion (combining independent model outputs). However, practical implementation must overcome significant limitations, including missing modalities, asynchronous sampling rates, sensor failures, and differences in temporal resolution across devices [50]. In the future, the ability to integrate these multimodal sensor outputs seamlessly with Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) could transform raw sensor data into a comprehensive and actionable decision support tool for farmers [82, 83].

Core Applications in Cattle Welfare, Health, and Behavioral Analytics

Translating high-dimensional sensory data and complex algorithmic outputs into actionable biological insights is the ultimate objective of PLF. These core applications will be able to shift the focus from herd-level averages to individual-level baselines by proactive management of cattle welfare, metabolic health, and physical comfort.

Locomotion Scoring and Automated Lameness Detection Systems

Lameness is a major welfare and economic problem in dairy production, affecting milk yield, fertility and causing chronic pain, and is one of the most severe endemic ones in the dairy industry worldwide. In the past, mobility has been evaluated subjectively by human observers that are time-consuming and have a high degree of inter-observer variability [66, 84]. To overcome this, automated lameness detection systems are based on deep learning and computer vision to obtain objective metrics describing the motions.

To detect important anatomical parts (head, back, legs, and hooves) during walking, recent approaches use advanced object detection models, such as YOLOv5, to produce accurate locomotion-related scores from stride length and step frequency [66]. Furthermore, the 3D depth camera can be used for the analysis of the spine curvature and the backline spline modeling which can help identify arching backs even in the pre-clinical stages, which is a good indicator of hoof lesions [24]. However, when evaluating lameness, it is critical to explicitly differentiate between the detection of currently clinical animals, the classification of severity, and the prediction of lameness prior to clinical manifestation. Claims regarding "pre-clinical" prediction require exceptionally strong evidence and clearly defined reference standards [15]. In addition, 12 specific key points are mapped along the spine and used to subjectively evaluate the curvature in the back shape related to the Locomotion Scoring System (LCS) [85]. The accuracy of kinematic parameters can be further enhanced by ensemble learning of these key points derived motion features [86]. Single-stream long-term optical flow CNN has shown high accuracy (up to 98.24%) for the spatio-temporal analysis of a lame cow's gait by processing motion vectors across multiple seconds of video [76] to detect subtle abnormalities that are often overlooked by human observers. Nevertheless, relying solely on overall accuracy can be highly misleading in imbalanced datasets. A rigorous evaluation must incorporate sensitivity, specificity, precision, recall, F1-score, the Area Under the Receiver Operating Characteristic curve (AUROC), and class distribution [15]. In practical welfare applications, the consequences of misclassification differ significantly: false negatives leave suffering animals untreated, whereas false positives may lead to alert fatigue and unnecessary interventions [87]. Therefore, automated alerts should generally be interpreted as risk-stratification signals rather than definitive diagnoses, and PLF performance should be evaluated not only through conventional algorithmic metrics but also through time-to-detection, time-to-action, clinical confirmation, and the effectiveness of the resulting intervention [9]. Their introduction is not only a technological achievement but also an economic imperative: bio-economic simulation models show that the economic and welfare advantages of multi-class, sensor-based sub-optimal mobility (SOM) alerts are significantly

greater than those gained by delayed, humans-only binary classification [87].

Ingestive Dynamics, Metabolic Health, and Disease Surveillance

Ingestive behavior is an important part of the health, productivity and welfare of the rumen. Additionally, computer vision systems using YOLOv8 can provide non-invasive ways to track feeding time and frequency to serve as health metrics [88]. Furthermore, using Spatio-Temporal Graph Convolutional Networks (ST-GCNs) enables accurate differentiation between affiliative and agonistic social interactions, surpassing the traditional use of static proximity thresholds [89]. Automated feeding systems like the Intergado electronic feeder and bunk scanners with lidar sensors, give continuous data on the individual feed intake, meal frequency and bunk attendance [41, 90]. Smart water point loggers track the drinking kinetics constantly, complemented with feeding data. In fattening units, dynamic changes of drinking behavior act as good, non-invasive, early warning signals for infectious diseases like BRD [54] as drinking behavior is very sensitive to physiological stress. In addition, electronic drinkers can automatically identify social dominance hierarchies based on agonistic replacement and resource guarding, thereby allowing for access to food equally by cows [52]. Furthermore, the interpretation of sensor-derived feeding and rumination information should account for lactation stage and nutritional management, since productive responses to dietary interventions can differ substantially across days in milk and may show particularly high biological variability during early lactation [91]. Precision monitoring may also contribute to post-implementation surveillance of sustainability-oriented nutritional interventions, since unexpected changes in feed intake, rumination activity, or milk production could provide early signals of potential adverse responses requiring veterinary investigation [92].

In the context of disease monitoring, wearables and computer vision serve as a never-ending examination process. Neck-mounted sensors can detect reductions in rumination and activity time, providing early warning of tick-borne diseases such as anaplasmosis, days before clinical signs are apparent [93]. Furthermore, deep learning has transformed the monitoring of respiratory diseases; for example, the Vision Transformer framework can automatically score the visual health of calves by analyzing the pattern of eye/nasal discharge and ear posture from a smartphone photograph of the calf [75]. Likewise, end-to-end VideoMAE models can continually estimate respiratory rates using RGB videos, which can directly serve as a physiological indicator of heat stress and pneumonia without manual counting [26]. Beyond behavioral sensors, routinely collected milk spectral information may provide an additional non-invasive layer for metabolic surveillance, although current predictions of BHB and NEFA appear more appropriate for herd-level risk screening than for precise individual diagnosis [94].

Biometric Phenotyping, Growth Profiling, and Individual Identification

Continuous monitoring of the welfare of individual animals depends on having a non-invasive method of animal identification (identification and re-identification) which would eliminate the pain, tissue damage and stress that result from traditional animal ear tagging and hot iron animal branding. However, it is important to emphasize that biometric identification itself is not a direct welfare outcome. Rather, its contribution is strictly infrastructural; it acts as the foundation that

enables continuous, individual-level welfare monitoring [45]. The advent of deep learning has led to a quick shift to biometric facial recognition and morphological identification. In addition, deep metric learning on 3D depth information offers a universal, color-independent identification framework, which also performs better under cluttered conditions than traditional RGB-based approaches [38]. Visual Biometrics is a field of innovation that's on a roll. Deep parts are based on side-view images, and Siamese NN for specific anatomical key points helps to identify color-independent for solid-colored herds [95, 96]. Under the UV camera, an invisible sunscreen pattern is used in specialized camera setups for identification and tracking of digital dermatitis, over a long time [97]. Furthermore, while advanced camera systems are increasingly used without the need for physical tags, biometric facial identification (recognizing who the animal is) is a fundamentally separate computational task from facial-expression-based affect assessment (measuring the emotional condition and general wellbeing of the animal), and the two must not be conflated [78, 98].

In the case of breed-specific applications, improved YOLOX algorithms are used, which are tailored to the unique black-and-white coving coat patterns of Holstein cows, for enhanced tracking accuracy [69]. Biometric identification in beef feedlots uses high-resolution muzzle print images as the bovine "fingerprints" and has been shown to produce highly accurate recognition rate at the muzzle level, potentially providing an alternative to RFID technology [79, 99]. Moreover, the "Open-Set Recognition" (OSR) models can be applied to correctly identify known animals and correctly identify new, unknown animals appearing in the field of view [100].

In addition to identification, computer vision can also provide high throughput biometric phenotyping. Multi-view stereo vision and ToF cameras automatically generate 3D point clouds for measuring the wither height, hip height, and chest girth [30, 40]. In beef finishing operations, the use of these composite morphological measurements combined with Spatial and SCA-ConvNet enables stress-free, highly accurate prediction of the live weight [74] and estimation of carcass traits [42].

Reproductive Events, Lifecycle Monitoring, and Micro-Environmental Comfort

The micro-environment inside a barn is directly related to cattle welfare and longevity. 3D computer vision is an important welfare application in assessing free stall cubicle comfort. Automated systems offer objective measures of the "adequacy of stall design" and "physical distress" by quantifying abnormal motion patterns and collision events through 3D pose estimation during posture transitions (lying-to-standing, standing-to-lying). Furthermore, computer vision systems based on YOLO and HRNet have been introduced to determine the use of mechanical brushes, identifying grooming patterns as a positive sign of welfare, promoting relaxation, maintaining good coat condition, and reducing stress [70].

The cow and calf are at a high risk during certain life stages, especially parturition. High-frequency tail-raising activities that are characteristic of stage-one labor are recorded by wearable, tail-mounted accelerometers, and machine learning classifiers can provide a reliable prediction of calving time to facilitate timely human intervention and reduce the incidence of dystocia and stillbirths [49]. Longitudinal ear-tag accelerometer monitoring has also shown potential for reproductive decision support, since post-insemination patterns of rumination and lying behavior may differ according to subsequent pregnancy status and could

contribute to the development of non-invasive early reproductive alerts [101]. While the accurate prediction of calving can significantly support welfare through timely veterinary intervention, the clinical actionability of automated alerts depends heavily on their specificity. High rates of false alarms can prompt unnecessary or disruptive interventions, which may induce additional stress to the animal; thus, highly specific alerting thresholds are essential [9]. Lastly, forecasting and buffer for environmental stress is crucial. Machine learning can effectively model environmental variables and predict heat seeking behaviors as a proxy indicator of heat stress in highly susceptible individuals, before they reach physiological collapse, such as young dairy calves [87]. Expansion of PLF beyond lactating cows should also consider replacement heifers, in which the longitudinal integration of growth rate, body condition, feed intake, and digestive indicators may facilitate earlier recognition of nutritional and developmental imbalances [102]. Furthermore, future PLF frameworks could further integrate longitudinal reproductive indicators with nutritional, environmental, and behavioral data, since reproductive outcomes such as services per conception and days open provide biologically and economically relevant information for evaluating long-term responses to management and nutritional interventions [103]. Sensor-based prediction of heat stress should be interpreted against the complex physiological response to thermal load, which involves changes in feed intake, oxidative balance, immune function, metabolism, reproductive performance, and productive responses [104].

Extensive Grazing Systems, Virtual Fencing, and End-of-Life Welfare Management

While intensive indoor dairy and beef operations have historically driven the development of PLF, applying digital technologies to extensive grazing systems presents a unique set of logistical and environmental challenges. Furthermore, extending these technologies beyond the farm gate to cover the end-of-life stages is increasingly recognized as a critical frontier for holistic animal welfare.

Precision Rangeland Management and Extensive Grazing Tracking

The welfare effects of using digital data loggers and virtual fencing under pasture conditions have been well summarized in recent literature with both operational and technical arguments needing careful consideration [18]. In large range areas, it is difficult to monitor animal welfare and behavior because of the wide range of geographical areas, unfavorable climate and low human animal interaction. To overcome these obstacles, remote spatial tracking networks are predominantly reliant on GPS collars. The actual distance grazed by livestock is, however, a challenge to estimating the correct distance. Studies have shown that short sampling intervals significantly overestimate distance traveled because of sum of total GPS coordinate error, and long sampling intervals are likely to underestimate distance traveled because they do not account for the meandering of grazing paths [56].

Modern systems use sophisticated spatial algorithms, such as KDE [57] and GIS to convert raw spatial data into meaningful information for farm management. These methods provide accurate data to the development of "Core Areas" which are areas most intensively used by the herd, which can provide useful information for pasture use, shade-seeking and areas liable to soil erosion [55, 57].

It is also important to ensure distribution of resources in these expansive areas. A RFID water infrastructure, which features antennas in the water and a continuous record is maintained of individual cattle presence at water points, ensures the optimal grazing distribution in a semi-arid rangeland environment [53]. Nutritional management is also becoming digital; the use of precision supplementation feeders (e.g., the Super Smart feeder) in pasture-based systems has demonstrated that grazing calves can be successfully trained using associative learning to use automated infrastructure to manage allocations of individual nutrients [105].

The final step of spatial tracking in PLF is the creation of VF technology. VF controls cattle movement without physical barriers by using GPS neckbands that provide a safe audio alarm when the animal is in proximity to a programmed boundary, and an electrical shock after the alarm. While some behavioral studies suggest that cattle can learn rapidly to interact with VF without significant differences in stress indicators compared to traditional electric tape fencing [65], this conclusion requires a more nuanced interpretation. The welfare outcomes of virtual fencing are highly conditional and depend heavily on the animal's learning capacity, individual variability, the predictability of audio cues, specific device configuration, the environmental context, and the frequency of exposure to electrical stimuli [106]. Furthermore, VF has a compelling double benefit: it allows for dynamic pasture management, and it excludes cattle from environmentally sensitive areas for more than 99% of the time, e.g. in areas of sapling regeneration. Recent developments have suggested computer vision and edge computing devices as an alternative, non-contact, real-time boundary enforcement solution in open pasture areas, to overcome these battery and connectivity challenges of GPS-based VF collars [107].

Digital Technology Deployment in Pre-Slaughter and Abattoir Environments

While the primary focus of PLF is on-farm monitoring, evaluating the pre-slaughter and abattoir environments is strictly justified within the scope of this review because the farm-to-slaughter continuum represents the final, most critical phase of the animal's lifecycle; excluding this phase would leave the holistic welfare monitoring framework incomplete [108]. The period between the farm gate and the slaughterhouse, specifically encompassing transport, unloading, and lairage, is widely recognized as the most stressful time in a bovine's life. Although monitoring these transition points is vital to both the welfare of the animal and subsequent meat quality, the use of automated monitoring systems in these specific areas has been comparatively slow to develop [39, 108].

In recent literature a paradigm shift is being encouraged, called "Precision Slaughter", that builds on the concepts of PLF to be practiced in the abattoir [108]. This novel concept incorporates sophisticated technologies such as intelligent image and sound analysis to constantly track pre-slaughter handling and crowding conditions. The use of continuous AI-based monitoring can help abattoir managers to objectively measure the interactions between humans and animals and detect localized stressors on the spot [68]. In the field of human activity recognition (HAR), AI models show impressive accuracy (JI (Jaccard index) > 0.90) when compared to human evaluators, with the ability to identify potentially dubious activities and to evaluate the results of pen crowding, which is a critical capability for monitoring the stunning efficiency and electric prod usage for 24/7, effectively flagging questionable events [109].

In addition, precision slaughter technologies strive to make the auditing of stunning efficiency and compliance fully automated, while also guaranteeing welfare is fully protected at the end-of-life phase. Slaughterhouses have significant environmental issues (e.g. high humidity, fluctuating lighting) and economic obstacles to the successful implementation of technological integration of slaughtering operations, but the advantages will be triple: reduce acute animal distress, standardize compliance with animal welfare requirements and enhance the mental and physical wellbeing of slaughterhouse workers [108].

Current Frameworks, Emerging Paradigms, and Socio-Technical Challenges

As PLF matures from experimental prototypes to commercial deployment, the focus of the scientific community is expanding beyond algorithmic accuracy. Current research emphasizes the integration of these technologies into standardized welfare frameworks, the rigorous validation of sensor outputs, the exploration of Generative AI, and the critical evaluation of the socio-technical and ethical implications of automated farming.

Transitioning Established Manual Assessment Protocols into Sensor-Based Frameworks

Over the years, several comprehensive assessment tools have been developed, e.g. Welfare Quality[®] protocol, which has been used as a prominent reference standard to evaluate the welfare of cattle. The protocols, however, rely on human observations, which are time-consuming, subjective and require punctuality, and are thus inherently constrained [12]. One of the major current paradigm shifts is the shift from the traditional multi-criteria manual protocols to continuous monitoring systems based on different sensors.

Recent concept studies have shown that machine learning techniques, like XGBoost, can combine the information of daily sensor data like activity level or health status data to automatically classify the individual cows' welfare status (good, moderate or poor) daily, virtually constructing a dynamic welfare indicator [12]. Although continuous monitoring of the welfare based on sensors is extremely helpful in providing an objective, up-to-date assessment of the welfare, there are considerable challenges.

Establishing Methodological Standards for Sensor Validation

The accuracy of the sensors in any PLF intervention is the base of the reliability of the intervention. Although the number of commercially available wearables has grown, a thorough scoping review found that there was a significant lack of standardization in the validation protocols found in the literature: very few studies (around 14%) met rigorous quality criteria based on precision, reproducibility, and lack of bias [45].

The current studies show a significant variation in statistical methods. While reporting agreement statistics such as Lin's Concordance Correlation Coefficient and Bland-Altman analysis is highly useful for continuous measurements, validation methods must strictly depend on the outcome being evaluated. For instance, classification systems require the reporting of sensitivity, specificity, predictive values, and appropriate discrimination or calibration measures, whereas repeated measurements necessitate statistical approaches that account for clustering within individual animals and farms [8]. Furthermore, external validity must be emphasized. Domain shift

across farms represents one of the major obstacles to translating PLF algorithms from isolated research datasets into reliable, routine welfare monitoring tools, necessitating dedicated cross-domain validation protocols [45]. Since cattle very quickly switch their behavioral budget in response to the context, unvalidated sensors can produce large amounts of data drift. Consequently, behavioral changes identified by wearable sensors should be considered candidate predictive signals and validated against appropriate biological reference standards; as an example, reproductive sensor patterns can be compared with subsequent ultrasound-confirmed pregnancy outcomes before being translated into farm-level alerts [101].

The New Horizon: Generative AI, LLMs, and RAG

Although predictive machine learning (PML) such as Random Forests or CNNs is widely used today, Generative AI (GenAI), and LLMs are the next big technological breakthroughs in smart farm management [82, 110]. The potential of GenAI for predictive modeling and automated management, especially for incorporating complex digital technologies into livestock housing, is unprecedented [110].

These LLM and multimodal machine learning models are well suited to the task of synthesizing and harnessing multiple data streams such as computer vision images, time-series sensor data, and tabular information on veterinary text [75] to generate actionable insights from raw data. AI-driven analytics are also undergoing transformation to include RAG systems that enhance decision-making in the farm by associating current on-farm data with extensive databases of veterinary knowledge [76]. Moreover, the synergy of AI and software engineering (e.g., symbolic AI, Domain-Specific Languages (DSL) used to build user-friendly web applications) is being used to help co-create practical tools for farmers based on complex mechanistic epidemiological models, such as those used in BRD control [111]. However, it must be explicitly noted that the application of GenAI and LLMs in PLF remains an emerging, highly speculative research direction. Deploying these models for veterinary and welfare decision-support introduces severe risks, including AI hallucinations, uncertainty regarding the provenance of veterinary information, cybersecurity vulnerabilities, and complex issues surrounding privacy and farm data ownership. Crucially, a plausible but factually incorrect LLM-generated recommendation can have immediate, detrimental consequences for animal welfare, raising unresolved questions about the ultimate responsibility for automated misdiagnoses [112]. Initial applications of LLMs in dairy-cattle research indicate that these tools can facilitate large-scale extraction and synthesis of behavioral information, although variable extraction and labeling accuracy demonstrates that human verification remains necessary, particularly when source data are inferred, heterogeneous, or ambiguous [112].

Socio-Technical and Ethical Threats of High Adoption

Due to the speed at which dairy and beef systems are being digitalized, there are emerging ethical and socio-technical questions that need to be examined carefully. The use of PLF technologies, if done without careful analysis, poses certain inherent dangers to animals. The literature highlights several risks, such as low levels of human-animal interaction, dependence on inaccurate sensor information, system failures, and the potential for automated alienation [18]. The transition from experimental PLF systems to routine farm implementation also requires consideration of end-user priorities, since recent

farmer-level evidence identifies installation costs and poor interoperability among platforms as important barriers, while health, calving, estrus, lameness, feeding, and rumination monitoring remain major priorities for future devices [113].

One central ethical issue is that the living, intelligent animals may be treated as mere resources or commodities for data collection or production. In addition to attempting to eliminate negative states, the "Five Domains Model" of animal welfare focuses on ensuring positive emotional experiences. Most PLF technologies are currently aimed at detecting disease or distress, tools to encourage or measure "positive" welfare states are still in their infancy [15]. There are solutions, however, that rely on technology. If properly applied, PLF technologies based on image and sound analysis can construct very precise 'digital representations' of an animal. This can effectively reduce the 'distance' between the individual animal and the manager, as herd size increases, and increases the visibility of the individual, 'closer' to the manager [8]. Furthermore, individual behavioral characteristics should also be considered when evaluating automated farming environments, since coping style may influence how cattle habituate to technologies such as Automatic Milking Systems, and may therefore contribute to inter-animal variability in behavioral indicators recorded by PLF platforms [114].

In conclusion, protecting welfare in the digital era hinges on continuing to have strong human oversight, adapting to cultural changes in the farming community, and emphasizing interdisciplinary cooperation to make sure technology is used to support the animals' welfare, not simply their production [7, 18, 83]. Environmental mitigation strategies must be evaluated alongside animal-level outcomes, wherein continuous PLF monitoring provides a vital surveillance layer to identify potential trade-offs between emission reduction, productive performance, health, and welfare [92]. In addition, the broader contribution of digital technologies to sustainable livestock production should be framed within a comprehensive food-system perspective that simultaneously accounts for greenhouse gas mitigation, resource use, food security, rural livelihoods, and the nutritional value of livestock-derived foods [115].

Figure 4 illustrates the holistic integration of state-of-the-art PLF systems within the Five Domains framework, mapping how physical inputs ultimately shape the animal's subjective mental state. Concurrently, Table (3) provides a granular breakdown of the specific digital proxies, AI algorithms, and scientific references driving each domain. However, this mapping must be interpreted cautiously. A digital proxy associated with a specific domain does not measure the corresponding subjective welfare state directly. For example, a behavioral proxy such as reduced feeding, altered movement, or vocalization can stem from multiple, overlapping causes. Therefore, it is critical to explicitly distinguish between the raw sensor measurement, the extracted behavioral or physiological proxy, the inferred welfare state, and the animal's actual subjective mental experience [18].

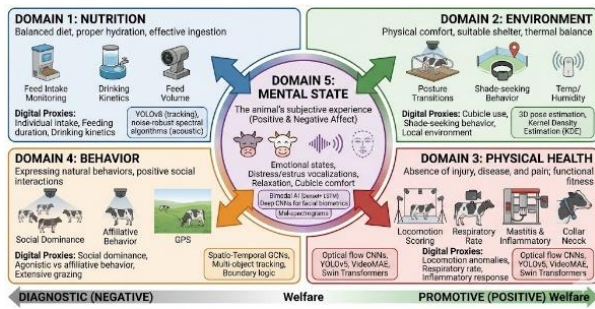


Figure (4): Integration of PLF technologies and AI within the Five Domains Model of animal welfare.

Future Research Directions and Conclusion

Future Research Directions

Despite the fast and transformative advancements in PLF technologies, various critical gaps must be addressed to confirm their sustainable and ethical deployment in the global dairy and beef industries. Future research should prioritize the following:

- **Robustness in Commercial Environments and Edge AI:** Many of the existing computer vision and machine learning models are trained in controlled or very specific experimental conditions which result in reduced accuracy when deployed outside of these constrained conditions and in real-world farms with complex lighting, heavy occlusion and extreme climatic conditions [68]. The deployment scalability of intensive smart feedlots often is limited by intermittent connectivity due to limited connections and the need for robust communications in harsh environments [117]. Complex lighting conditions, environmental noise and background interference need to be addressed explicitly in AI approaches [21]. On the other hand, short-range bioassessment in robotic dairy farms (RDF) is a promising way toward achieving totally automated veterinary support [98]. Future work should aim to create more general-purpose, lightweight models (such as improved YOLO), that can run on devices located in the barn or pasture without relying heavily on the cloud and without incurring latency issues [68, 107].
- **Quantifying "Positive" Welfare:** The current PLF paradigm is overwhelmingly diagnostic, focusing on the detection of

negative states such as lameness, heat stress, or infectious diseases [15]. Future technological frameworks must pivot toward assessing the "Five Domains Model" holistically by developing algorithms that quantify positive emotional states. Monitoring environmental enrichment interactions, such as mechanical brush use, play behavior, and positive social affiliations, will be crucial for advancing beyond mere survival toward genuine animal wellbeing [70, 116]. However, it is essential to recognize that brush use or affiliative behaviors should not be automatically equated with a positive affective state. Rather, these measures currently represent candidate proxies that require rigorous biological and psychological validation to ensure they accurately reflect the animal's subjective positive experience [116].

- **Standardization, Interoperability, and Validation:** Future research must implement rigorous, standardized protocols to systematically report sensor precision, bias, and reproducibility, with a much stronger emphasis on prospective multi-farm validation, the creation of shared benchmark datasets, unified reporting standards, and the independent evaluation of commercial devices [45]. Additionally, establishing open-source data interoperability standards is crucial for the industry to facilitate the seamless integration of heterogeneous data streams—such as combining Automatic Milking System (AMS) metrics with wearable accelerometer data and computer vision outputs—into unified herd management platforms [52]. Technically, the interoperability challenge extends far beyond merely combining different sensors; it fundamentally requires the strict harmonization of animal identifiers, timestamps, sampling frequencies, metadata, missing-data handling protocols, and semantic definitions across disparate platforms. Resolving these practical data-fusion issues is what will ultimately determine whether multimodal welfare monitoring can successfully operate at a commercial farm scale [113]. Standardization should extend beyond sensor validation to behavioral definitions and reporting practices, since heterogeneity in ethograms, measurement formats, and definitions of eating, rumination, and lying can limit cross-study comparisons and the reliable reuse of behavioral datasets for AI applications [112].

Table (3): Mapping state-of-the-art PLF technologies and AI models to the Five Domains Model of animal welfare assessment.

Welfare Domain	Digital Proxy / Behavioral Indicator	Sensor Technology Deployed	AI Framework / Algorithm Used	Current Paradigm Status	Key References
Nutrition	Individual feed intake, feeding duration, drinking kinetics, and foraging events (bites/chews).	Lidar bunk scanners, electronic feeders (Intergado), smart water loggers, bioacoustic microphones.	YOLOv8 (feeding tracking), noise-robust spectral algorithms (acoustic), and threshold-based loggers.	Diagnostic: Primarily detects reduced intake and acts as an early warning for diseases (e.g., BRD).	[41, 52, 54, 60, 88, 90]
Environment	Micro-environmental comfort, freestall cubicle collisions, and shade-seeking behaviors.	3D Depth cameras (RGB-D), indoor IoT environmental sensors, GPS collars.	3D pose estimation, machine learning environmental modeling, and KDE.	Preventive: Focuses on predicting heat stress and evaluating the adequacy of physical stall design.	[33, 34, 47, 57, 80]
Physical Health	Locomotion anomalies (lameness), respiratory rates, mastitis, and subclinical metabolic/infectious affections.	RGB video cameras, ToF, IRT, and wearable accelerometers.	Single-stream long-term optical flow CNNs, YOLOv5, VideoMAE, Swin Transformers, and XGBoost.	Diagnostic: Dominant focus of PLF; rapid detection of negative states and chronic pain.	[14, 26, 37, 66, 75, 76, 85, 93]
Behavior	Social dominance, affiliative vs. agonistic interactions, and extensive grazing distribution.	Indoor UWB, RGB cameras, GPS collars, and Virtual Fencing neckbands.	ST-GCNs, multi-object tracking, and boundary logic.	Mixed: Tracks both negative (agonistic) and natural/positive (grazing) spatial behaviors.	[51, 55, 58, 59, 89]

Welfare Domain	Digital Proxy / Behavioral Indicator	Sensor Technology Deployed	AI Framework / Algorithm Used	Current Paradigm Status	Key References
Mental State	Emotional state variations, distress or estrus vocalizations, and relaxation (grooming).	High-resolution facial cameras, bioacoustic circuits, and mechanical brush sensors.	Bimodal AI (DenseNet + LSTM), deep CNNs for visual biometrics, and audio mel-spectrograms.	Emerging Positive: Actively shifting toward assessing positive emotional experiences and relaxation.	[61, 62, 70, 78, 116]

Abbreviations: AI, artificial intelligence; BRD, bovine respiratory disease; CNN, convolutional neural network; GPS, Global Positioning System; IoT, Internet of Things; IRT, infrared thermography; KDE, kernel density estimation; LSTM, long short-term memory; PLF, precision livestock farming; RGB, red-green-blue; RGB-D, red-green-blue-depth; ST-GCN, spatio-temporal graph convolutional network; ToF, time-of-flight; UWB, ultra-wideband.

– **Generative AI and Human-Centric Decision Support:** The sheer volume of high-dimensional data generated by PLF systems can overwhelm farm operators. Future research should explore the integration of GenAI, LLMs, and RAG to translate complex data streams into conversational, context-aware decision-support tools [83, 118]. These tools must be co-designed with farmers to ensure high digital literacy adoption and practical field utility [111]. Future PLF development should adopt a farmer-centered design strategy in which technical performance is considered together with affordability, interoperability, usability, and investment capacity, since unequal access to digital innovation may progressively widen technological differences among dairy production systems [113].

Conclusion

Digital technologies and AI are changing the face of cattle management, marking a paradigm shift in agricultural science. The development of computation has gone far beyond statistical models to more sophisticated deep learning systems, such as ViTs and multimodal sensor fusion, allowing complex physiological and behavioral state classification. While many of these models have demonstrated high accuracy and near real-time inference under controlled conditions, it must be acknowledged that performance still varies substantially across different applications and experimental settings.

The transformation of the livestock industry into a digital sector is not only a technical process but a complex socio-technical and ethical shift. Digital technologies should not be considered a substitute for human stockmanship, but rather as a powerful tool which complements human observation. Ultimately, the principal conclusion of this review is that promising algorithmic performance does not automatically guarantee robust welfare assessment under heterogeneous commercial conditions. Moving forward, the industry must clearly distinguish between mere technological capability, true biological validity, and actual operational readiness.

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