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REVIEW ARTICLE

Smart Solutions for Livestock Management and Health Monitoring

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ABSTRACT

Livestock are integral to global food security, contributing meat, milk, and eggs as vital protein sources while supporting millions of livelihoods and sustaining agricultural economies. However, conventional livestock management faces persistent challenges, including disease outbreaks, inefficient health monitoring, and unsustainable resource utilization. The convergence of Artificial Intelligence (AI), Internet of Things (IoT), Computer Vision (CV), and advanced Sensor Technologies is revolutionizing livestock farming through intelligent, real-time, and non-invasive monitoring systems. Smart ear tags and biosensors continuously capture physiological and behavioral data, while AI-driven analytics enable early disease detection, stress assessment, and productivity optimization. These innovations empower farmers with predictive insights for proactive decision-making, improving animal welfare and minimizing economic losses. Despite immense potential, technological adoption remains constrained by high costs, limited connectivity in rural areas, and interoperability issues among IoT devices. Developing scalable, affordable, and integrated AI-sensor frameworks can overcome these barriers and transform traditional livestock farming into a data-driven, sustainable enterprise. Such precision livestock management not only enhances productivity and resource efficiency but also supports global efforts toward resilient, ethical, and technologically advanced food systems. In this review, we discuss the diverse applications of AI, sensor, and computer vision technologies in livestock management, emphasizing their potential to advance precision farming, sustainability, and global food system resilience.

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INTRODUCTION

The global demand for food is projected to rise dramatically in the coming decades due to rapid population growth. The United Nations (2022) (https://www.un.org/en/desa/world-population-projected-reach-98-billion-2050-and-112-billion-2100) estimates that the current population of 7.6 billion will reach 8.6 billion by 2030, 9.8 billion by 2050, and 11.2 billion by 2100. This demographic expansion is expected to increase global food demand by 59-98%, with particularly sharp growth in demand for livestock-derived products such as meat, milk, and eggs (Valin *et al.,* 2014). By mid-century, total food requirements may grow by nearly 70%, while meat consumption alone is projected to rise by over 50% (Foley *et al*., 2011; https://www.unep.org/, 2023). This intensifying demand has accelerated the expansion of the livestock sector globally. However, such rapid intensification has serious environmental implications, contributing significantly to deforestation, land degradation, biodiversity loss, and approximately 14.5% of global greenhouse gas (GHG) emissions (Gerber *et al*., 2013; Rojas-Downing *et al.,* 2017). Moreover, climate-induced stress such as extreme heat, further exacerbates production inefficiencies by increasing disease prevalence, reducing fertility, and lowering feed quality and availability (Das, 2018; Kumar *et al.,* 2018). Therefore, the challenge is twofold: to enhance livestock productivity while ensuring environmental sustainability and animal welfare (Zhang *et al.,* 2021). In response, Precision Livestock Management (PLM) has emerged as a transformative paradigm for achieving sustainable intensification in animal agriculture. PLM leverages advanced digital technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data analytics, cloud computing, Computer Vision (CV), and sensor technologies to enable data-driven decision-making and optimize animal health, welfare, and production efficiency (Chaudhry *et al.,* 2020; Iwasaki *et al.,* 2019; Mansoor and Chung, 2024; Dawkins, 2025). AI-based systems facilitate predictive analytics, enabling the early detection of behavioral or physiological anomalies and supporting proactive health management and performance optimization. Sensor technologies continuously capture environmental and physiological data, such as body temperature, activity, humidity, and air quality, providing actionable insights into animal comfort and resource utilization (Banhazi *et al.,* 2012; Tzanidakis *et al.,* 2023). Similarly, CV techniques offer non-invasive, real-time behavioral and morphological monitoring, identifying changes in locomotion, feeding, or posture that may indicate disease or welfare issues (Gupta, 2024; Famuyiwa *et al.,* 2024). Recent progress in AI-CV-sensor integration has enabled the development of livestock biometrics for automated extraction of physiological and behavioral indicators related to welfare and productivity (Fuentes *et al.,* 2022). Despite these advances, several constraints hinder the widespread adoption of precision technologies. High capital costs, data privacy concerns, limited rural connectivity, and the lack of standardized interoperability across IoT platforms remain major challenges (Karunathilake *et al.,* 2023). Furthermore, the ethical implications of constant surveillance and automation in livestock systems warrant deeper examination. Addressing these challenges through low-cost, scalable, and ethically guided frameworks will be critical for realizing the full potential of PLM in achieving sustainable, welfare-oriented livestock production systems.

Scope and Objectives: This review provides a comprehensive and critical analysis of the convergence of Artificial Intelligence (AI), Computer Vision (CV), and Sensor Technologies (ST) in advancing Precision Livestock Management (PLM). It offers an integrated perspective that extends beyond individual applications emphasizing the synergistic potential of AI-CV-sensor fusion in achieving data-driven, ethical, and sustainable livestock management.

The objectives of this review are to:

- Synthesize recent advancements in AI-, CV- and sensor-based approaches for real-time monitoring of animal health, behavior, and environmental parameters.
- Examine applications of these technologies in disease detection, productivity improvement.
- Critically evaluate their contributions toward sustainable and ethical livestock systems.
- Identify existing gaps and challenges, including scalability, cost, data governance, and interoperability, and propose future directions integrating IoT, robotics, and deep learning innovations.

The remainder of this paper is structured as follows:

Section 2 (Synergistic Technologies in Precision Livestock Management): Overview of AI, CV, and ST as fundamental components of PLM.

Section 3 (Algorithmic Frameworks: Machine Learning and Deep Learning): Key computational models, including Deep Learning (DL), Convolutional Neural Networks (CNNs), Region-Based CNNs (R-CNNs), You Only Look Once (YOLO), and Multi-Layer Perceptrons (MLPs).

Section 4 (Applications of Integrated Smart Technologies in Livestock Management): Practical applications in livestock monitoring, behavior analysis, disease detection, and breed identification.

Section 5 (Discussion): Synthesis of findings, critical assessment of performance and feasibility.

Section 6 (Limitations, Challenges, and Future Perspectives): Limitations, ethical considerations, and potential solutions for sustainable adoption.

Section 7 (Conclusion): Summary of insights and recommendations for advancing integrated AI-driven livestock management.

Section 8 (Future Directions)

Synergistic Technologies in Precision Livestock Management: The integration of AI, CV, and ST has transformed PLM, ushering in a new era of data-driven, intelligent farming (Fig. 1). These complementary technologies generate continuous, high-resolution data that enable real-time decision-making, predictive health management, and individualized animal care.

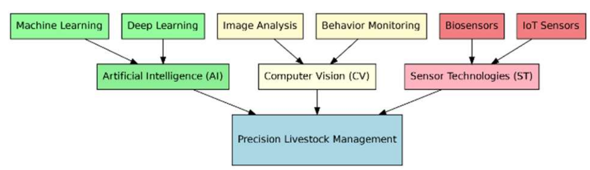

Fig. 1: Schematic representation of AI-based technology in Precision Livestock Management. The diagram illustrates the integration of AI, CV, and ST as the core components of PLM.

By automating routine monitoring and integrating environmental, physiological, and behavioral data, they enhance efficiency, sustainability, and animal welfare across diverse production systems (Fuentes *et al.,* 2022). Collectively, AI, CV, and ST establish a cohesive digital framework that supports proactive, adaptive, and welfare-oriented livestock management.

Artificial Intelligence: AI leverages computational tools, ML, and intelligent systems to improve operational efficiency and decision-making. Applications include precision farming, disease detection, yield prediction, and livestock management (Shaikh *et al.,* 2022; Varshney *et al.,* 2021; Cockburn, 2020). By integrating multimodal data from physiology, behavior, and the environment, AI enables predictive analytics for early anomaly detection and adaptive management. However, challenges such as heterogeneous data formats, limited public datasets, and the need for robust model validation hinder large-scale implementation (Berckmans, 2017; Rodríguez Espinosa *et al.,* 2016).

Computer Vision: Computer Vision (CV) enables automated and non-invasive monitoring of livestock through the interpretation of visual data. It supports a wide range of analytical tasks, including image classification, object detection, segmentation, and tracking (Szeliski, 2022; Schmidt *et al*., 2024). In animal agriculture, computer vision technologies are increasingly employed to enhance monitoring, management, and decision-making processes. Major applications include: (1) Animal identification; recognizing individual animals using facial or body pattern recognition; (2) Health monitoring; detecting illness, stress, or injury through posture and movement analysis; (3) Behavior analysis; monitoring feeding, resting, and social behaviors to assess welfare and productivity; and (4) Automated counting; tracking and quantifying animals for management and inventory purposes (Fig. 2).

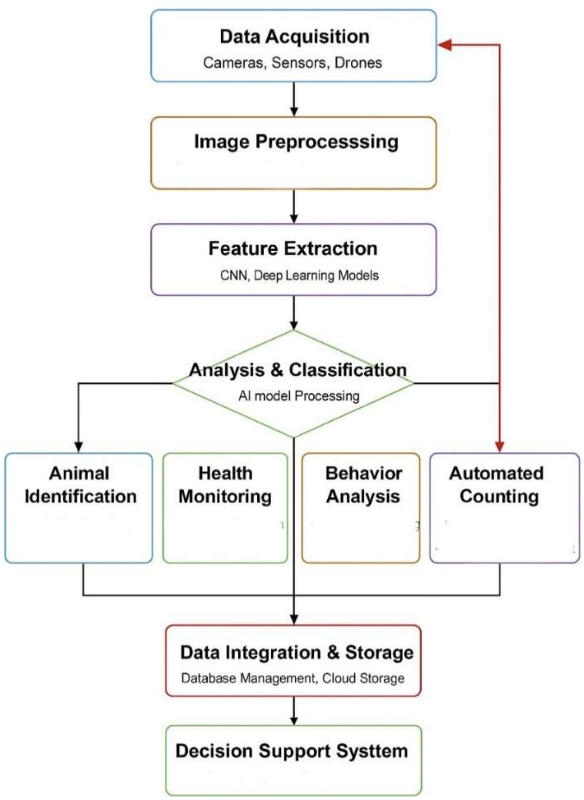

Fig. 2: Application of computer vision in livestock and animals.

Sensor Technologies (ST): Sensors detect and measure biological, chemical, and physical parameters, providing continuous, real-time data essential for precision livestock management (Neethirajan, 2020). Integrated within IoT frameworks, these devices monitor animal health, behavior, and environmental conditions, enabling data-driven and timely interventions. In livestock systems, sensors are either animal-mounted (e.g., accelerometers, Wireless Intra-ruminal Sensors, RFID tags) or environment-based (e.g., temperature, humidity, and gas sensors). The collected data are processed through AI and machine learning models to detect anomalies, predict diseases, and optimize management practices. Applications include gait analysis using force plates, welfare assessment via biosensors, and behavior tracking with sound or motion detectors (Rutten *et al.,* 2013; Neethirajan, 2017). While sensor-based monitoring enhances productivity, welfare, and sustainability, challenges such as data integration, false-positive alerts, and dependence on technology continue to limit widespread adoption.

Algorithmic Frameworks: Machine Learning and Deep Learning: Algorithmic frameworks such as ML and Deep Learning (DL) form the core of modern artificial intelligence systems, enabling data-driven predictions, pattern recognition, and intelligent decision-making across various domains. Machine Learning involves algorithms that learn from data to make predictions or classifications without explicit programming. It encompasses supervised, unsupervised, and reinforcement learning approaches (Morales and Escalante, 2022). Supervised learning methods, including Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (kNN), are widely used for classification and regression tasks, while unsupervised methods such as k-Means clustering and Principal Component Analysis (PCA) help uncover hidden patterns in unlabeled data. Reinforcement learning focuses on optimizing actions based on feedback from the environment. Popular ML frameworks such as Scikit-learn, XGBoost, and LightGBM provide efficient tools for implementing these algorithms (Abbadi *et al.,* 2020). A key limitation of traditional ML approaches is their reliance on manual feature engineering, which involves selecting, extracting, and designing relevant input features to enhance model performance. ML has been successfully applied in various areas of livestock and agricultural research, such as predicting animal body weight (Sarini *et al.,* 2023) and classifying livestock diseases (Grace *et al.,* 2024; Džermeikaitė *et al.,* 2025). The commonly used machine learning techniques are illustrated in Fig. 3.

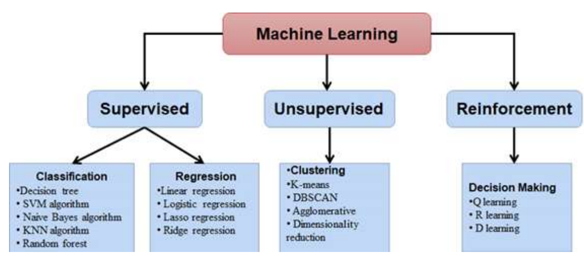

Fig. 3: Machine learning classification techniques.

Deep learning (DL): A subset of AI, DL addresses complex problems using layered neural network architectures capable of automatically extracting high-level features from data (Deng & Yu, 2014). This capability significantly reduces the need for manual feature engineering, making DL more powerful than traditional ML approaches. The DL prediction process typically follows two phases: in the training phase, the algorithm learns from a dedicated dataset, and in the validation phase, its performance is evaluated using a separate dataset. The trained model, comprising the algorithm and its learned parameters, is then employed to predict outcomes and support decision-making. Despite this seemingly straightforward workflow, developing accurate DL models presents several challenges, including selecting suitable architectures, configuring optimal training networks, and managing large and complex datasets. Advancements in computing technologies have enhanced the application of DL for monitoring animal needs and behaviors (Mahmud *et al.,* 2021). In precision cattle farming, DL has been successfully applied for fly detection (Psota *et al.,* 2021), lameness detection (Kang *et al.,* 2020), and mastitis diagnosis (Xudong *et al.,* 2020) using ground-based images. Additionally, DL has been utilized for body weight prediction and animal counting using UAV imagery (Gjergji *et al.,* 2020; Xu *et al.,* 2020). Deep neural network-based object detection methods generally fall into two categories:

1. Two-stage detectors, which combine region proposal and convolutional operations (e.g., R-CNN).
2. One-stage detectors, which directly perform object detection as a regression task (e.g., YOLO).

Among various DL architectures, the most widely used models in livestock applications include CNN, R-CNN, and YOLO.

Convolutional Neural Network (CNN): A CNN is a deep learning architecture consisting of three primary layers: convolution, pooling, and fully connected (FC) layers (Kamilaris and Prenafeta-Boldú, 2018a; 2018b) (Fig. 4).

The convolution layer extracts diverse spatial features from input images using multiple filters. The pooling layer reduces the spatial dimensions of the convolved features, minimizing computational complexity while retaining key information. Finally, the fully connected layer integrates the extracted features through weighted neurons to perform classification or prediction.

R-CNN: It represent a class of deep learning models designed for object detection in computer vision. Introduced by Girshick *et al.,* (2015), R-CNN applied a high-capacity CNN to generate bottom-up region proposals, laying the foundation for modern two-stage detection frameworks. The fundamental concept of R-CNN involves two sequential stages: region proposal and object classification (Ibraheam *et al.,* 2021). In the first stage, R-CNN identifies candidate regions likely to contain objects, typically using the Selective Search algorithm. Each proposed region is then processed through a pre-trained CNN for feature extraction (Fig. 5).

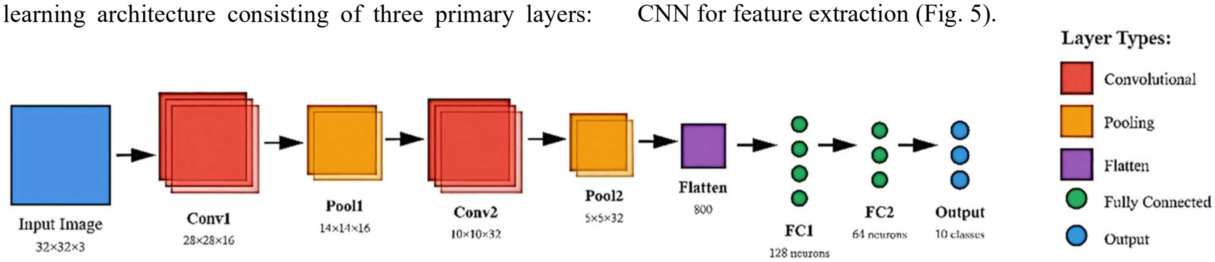

Fig. 4: Basic CNN architecture.

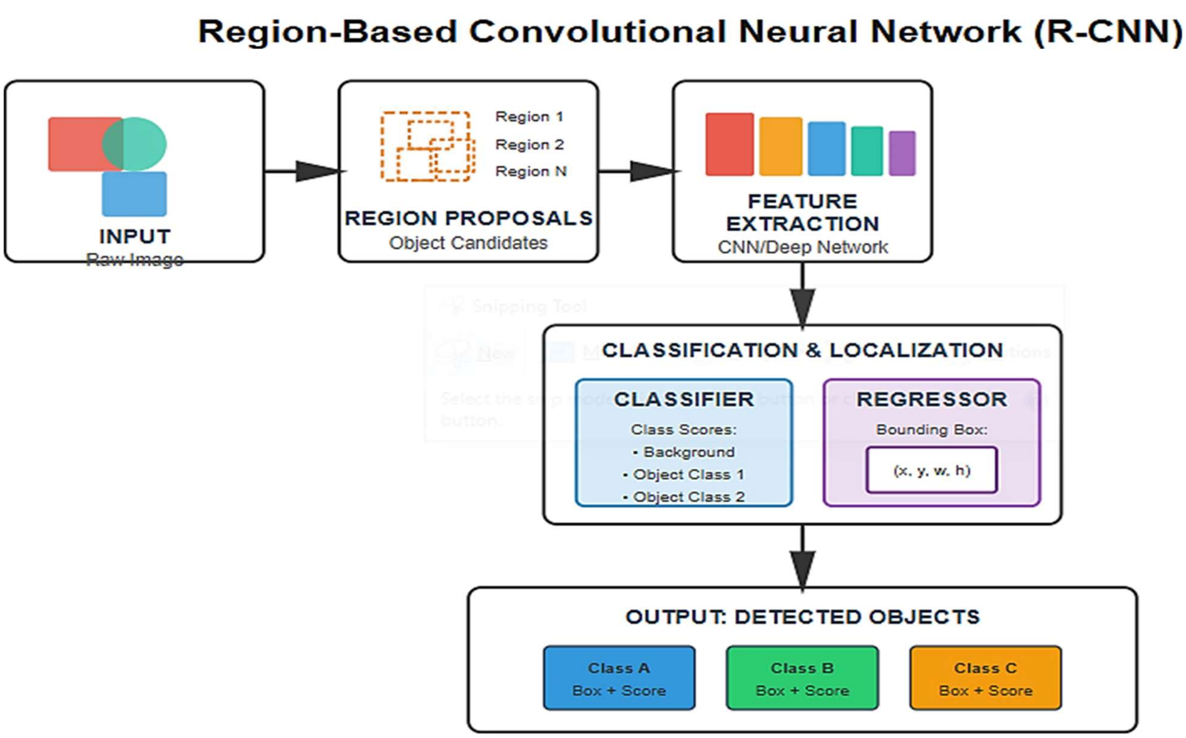

Fig. 5: Region-based Convolutional Neural Network (R-CNN) Architecture. Schematic of the Region-Based Convolutional Neural Network (R-CNN) showing region proposal generation, CNN-based feature extraction, and subsequent classification and bounding-box regression to produce final object detections.

YOLO: is a one-stage object detection algorithm that analyzes an entire image using a single neural network to predict object classes and locations directly (Shafiee *et al.,* 2017). YOLO is widely applied in large-scale target recognition and local object identification tasks, offering high processing speed compared to traditional methods (Yan *et al.,* 2021). While one-stage algorithms like YOLO tend to have lower accuracy for occluded or small objects, improvements such as YOLOv5 increased processing efficiency in deeper networks (Zhu *et al.,* 2021). To address multi-scale and small-object detection challenges, Adaptive Spatial Feature Fusion (ASFF) was introduced (Feng and Yi, 2022). The integration of YOLOv5 with ASFF (YOLOv5-ASFF) enhanced feature fusion and improved cattle detection performance (Qiao *et al.,* 2023). Recently, Balderas *et al.* (2025) developed a cattle identification system using YOLOv8, employing CLAHE for image enhancement, ORB for feature extraction, and FLANN for feature matching, achieving 88% accuracy across 25 cattle.

Multi-Layer Perceptron (MLP): MLP is a type of artificial neural network (ANN) characterized by multiple layers of interconnected neurons arranged in a feedforward manner, allowing unidirectional information flow from input to output (Riedmiller & Lernen, 2014). The input layer represents the input features, hidden layers learn complex nonlinear relationships, and the output layer generates predictions, with node count depending on the task (binary or multiclass classification). An MLP's architecture is defined by the number of hidden layers, neurons per layer, and activation functions such as sigmoid, tanh, or ReLU. Training is typically supervised using backpropagation, with algorithms including scaled conjugate gradient (SCG), Levenberg-Marquardt (LM), gradient descent with variable learning rate (GDX), and resilient backpropagation (RP) (Møller, 1993; Ranganathan, 2004; Dao & Vemuri, 2002; Naoum *et al.*, 2012). According to the universal approximation theorem, MLPs can approximate any continuous function given sufficient hidden neurons. However, their performance is highly dependent on network architecture, hyperparameter tuning, and the quality of training data (Kaveh & Mesgari, 2023).

Applications of Integrated Smart Technologies in Livestock Management: The integration of advanced technologies such as AI, CV, and sensor systems has unlocked a multitude of innovative applications in livestock management. AI-powered analytics can precisely analyse large volumes of data collected from sensors and CV systems to monitor and optimise various aspects of animal health, welfare, and productivity. AI algorithms are capable of detecting subtle behavioural or physiological changes in animals, allowing for early disease detection and timely intervention (Saida *et al.,* 2025; Faye *et al.,* 2025) (Fig. 6). CV technology facilitates real-time monitoring of livestock behaviour, posture, and interactions, offering valuable insights into social dynamics and welfare assessment (Fernandes *et al.,* 2020; Guarnido-Lopez *et al.,* 2024). Moreover, sensor-based monitoring systems provide accurate measurements of environmental parameters within livestock facilities, enabling proactive adjustments to enhance animal comfort and well-being (van Erp-van der and Rutter, 2020; Sanjeevi *et al.,* 2020).

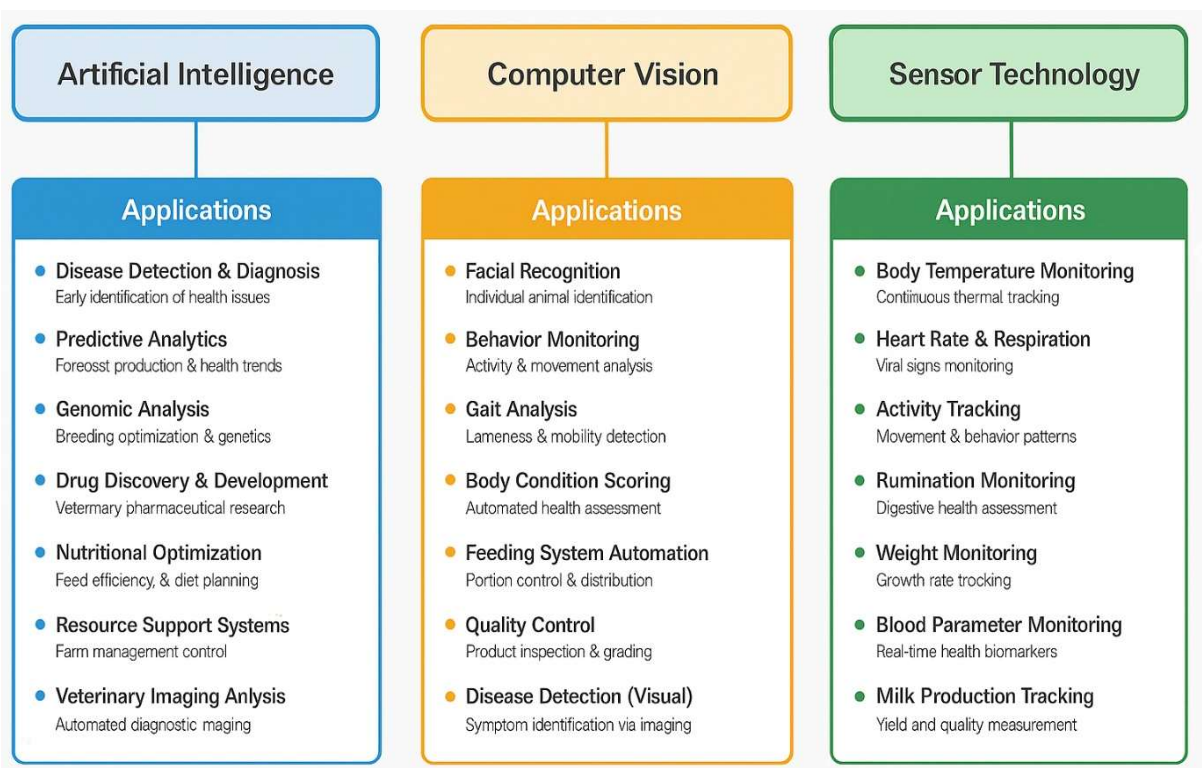

Fig. 6: Applications of AI-based technology in animal livestock.

These technologies collectively enhance the ability to monitor animals continuously, detect abnormalities early, and optimize management interventions. The key reasons highlighting the importance of combining these technologies in livestock health and performance are summarized in Table 1.

Table 1: AI and Cutting-Edge Technologies in Livestock Management

Problem/Task	Solution	Description/Use
Health Monitoring	AI-driven Analysis Early Disease Detection	AI algorithms process data from sensors and computer vision systems to monitor the health of individual animals. Early detection of signs of illness enables prompt veterinary intervention, enhancing overall welfare (Pawar *et al.,* 2024)
Preventive Care	Behavioural analysis (CV insights)	CV observes and interprets animal behaviour, providing insights into stress levels, social interactions, and overall well-being. This helps tailor management practices for improved welfare (Fernandes *et al.,* 2020; Guarnido-Lopez *et al.,* 2024).
Precision Feeding	AI-optimised feeding strategies	Integration of AI, CV, and sensors allows precise feeding based on individual nutritional needs, improving feed efficiency and reducing waste (Seo *et al.,* 2025).
Behavioral Monitoring	Sensor-Driven Data	Sensors monitor animal behaviors (Ding *et al.,* 2025).
Disease Prevention	Early Detection	AI's analytical capabilities, combined with data from sensors and computer vision, allow for the early detection of disease indicators. Timely identification enables proactive measures, preventing the spread of illnesses and minimizing their impact on animal health (van Erp-van der and Rutter, 2020; Sanjeevi *et al., 2020).*
Reproductive Management	Automated estrus and calving detection	CCV and AI track reproductive behaviours and fertility cycles, improving breeding success (Landim *et al.,* 2024; Santos *et al.,* 2022).
Remote Monitoring	Real-time health and performance insights	Remote sensors and edge-AI systems enable real-time livestock monitoring even in large-scale operations (Faye *et al.,* 2025).
Farm Management	Data-Driven Decision-Making	AI integrates multi-source data for disease prediction, feed optimisation, and resource management (Berckmans, 2017).

Therefore, the fusion of AI, computer vision, and sensor technology in animal health and performance provides a powerful toolkit for farmers, veterinarians, and researchers. It enables proactive health management, individualized care, and the optimization of farming practices, ultimately contributing to improved animal welfare and increased agricultural efficiency.

Smart Supervision and Data-Driven Management of Livestock: Sensor-based technologies have transformed livestock supervision and management by enabling real-time, continuous monitoring of physiological, behavioral, and environmental parameters crucial for animal well-being and productivity. Modern livestock facilities increasingly employ embedded and wearable sensors to capture data on temperature, humidity, air quality, feed and water intake, and animal movement (Egon and Oloyede, 2023). These smart sensors can also record individual animal metrics such as heart rate, rumination patterns, body temperature, and activity levels, providing a holistic view of animal health and comfort. By leveraging AI-driven data analytics, livestock managers can rapidly detect deviations from optimal conditions, such as heat stress, reduced rumination, or inactivity that may indicate illness or environmental discomfort (Li *et al.,* 2025a). The integration of sensor data enables predictive decision-making related to feed, ventilation, and hydration adjustments, thereby optimising resource utilisation and improving both animal welfare and farm efficiency. Fig. 7 illustrates a conceptual framework for sensor-based livestock monitoring. In this system, wearable sensors (collars, ear tags, leg bands) continuously measure physiological and behavioural parameters, while environmental sensors monitor barn or pasture conditions. Data are transmitted wirelessly to a central database or cloud platform, where AI and deep learning algorithms analyse the information to detect anomalies in behaviour, health, or environment. Based on these insights, automated or manual interventions, such as feed distribution, ventilation control, or virtual fencing, can be implemented to maintain optimal livestock conditions and performance.

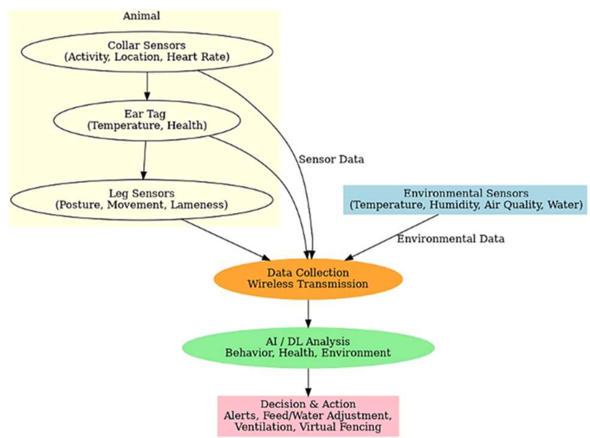

Fig. 7: Schematic representation of sensor-based livestock monitoring.

The widespread deployment of sensor and AI-driven systems across countries underscores the global importance of adopting advanced agricultural practices. A diverse range of livestock management solutions, spanning cattle, buffalo, sheep, and goats, demonstrates how digital tools are reshaping modern agriculture. From Australia's Data Muster, which uses sensors for calving prediction and individual animal monitoring, to Israel's Allflex SenseHub, which utilizes accelerometers for health, rumination, and estrus detection, these technologies represent the next frontier of precision livestock farming (PLF). Systems like New Zealand's eShepherd and Halter employ solar-powered, GPS-enabled collars to implement virtual fencing and behavior tracking, while USA's Vence provides cloud-based solutions for virtual paddock control and welfare monitoring.

These systems reflect a paradigm shift toward sustainable, automated, and welfare-oriented livestock management (mentioned in Table 2), integrating IoT, computer vision, GPS, and AI for decision support, efficiency improvement, and environmental monitoring.

Table 2: Cutting-edge software solutions utilized for the supervision and management of livestock.

System/tools	Species	Country	Technique used	Outcomes/features	References
Data Muster	Cattle	Australia	Sensor	Claving prediction, individual animal monitoring, Monitoring weight and suitability for the market, identifying fast-growing and fertility	https://www.datamuster.net.au/
SenseHub Feedlot	Cattle	USA	Electronic ear tag utilizing Artificial Intelligence	health management, sense animal temperature and activity	https://sensehubfeedlot.com/
smaXtec	Cattle	Austria	Accelerometer, thermometer	Feeding optimisation, calving detection and monitoring, heat detection, 24/7 monitoring, and early detection	https://smaxtec.com/en/
CERES Tag	Cattle	Australia	GPS-enabled ear tag	Monitor animal health effortlessly, estimate feed efficiency, Geofencing, and methane emissions	https://cerestag.com/
Digitanimal	Cattle, sheep, goats, and horses	Spain	GPS collars, Accelerometer, Thermometer	Tracking and monitoring system for livestock farms	https://digitanimal.com/?lang=en
Allflex SenseHub	Cattle	Israel	Accelerometer	Health, rumination, heat, calving, heat stress, and activity	https://www.allflex.global/livestock-monitoring/
dairymaster	Cattle	Ireland	Accelerometer	Activities: resting, feeding, rumination, and heat detection	https://www.dairymaster.com/products/moomonitor/
Peacock Technology (IceTag, IceQube and IceRobotics)	Cattle	UK	Accelerometer, machine vision, and artificial intelligence	Lameness, activity, resting and heat detection	https://www.peacocktechnology.com/
Moocall	Cattle	Ireland	Sensor-based	Calving alert and heat detection	https://www.moocall.com/
CalveSense	Cattle	Israel	Accelerometer	Calving	https://www.allflex.global/livestock-monitoring/
eShepherd	Cattle	New Zealand	Solar-powered, GPS-enabled neckband	Monitor, control, and guide livestock across farm by creating and employing virtual boundaries.	https://agersens.com/
Halter	Cattle	New Zealand	Solar-powered, GPS-enabled collars	Monitor grazing performance, Virtual fencing, monitor individual cow health, and heat detection	https://halterhq.com/
Vence	Cattle	USA	GPS collars	Monitor animal wellbeing, Virtual fencing, control animal movement, monitor grazing pattern	http://vence.io/
Nofence	Cattle, sheep and goats	Norway	GPS collars	Virtual fencing and monitoring	https://www.nofence.no/en
Cattle Muzzle Matching API	Cattle	India	Computer vision, AI camera	Accurate Identification, facial recognition, or muzzle matching, Easy Integration with Existing Cattle Management Systems	https://www.pixuate.com/products/cattle-muzzle
CattleMax	Cattle, buffalo	United States	Website	Cattle inventory management, health records, breeding management, and financial tracking.	https://www.cattlemax.com/
Rancher	Cattle, buffalo, sheep and goat	United States.	Website	inventory, health management, farm infrastructure management, grazing planning, and financial tracking for ranching enterprises.	https://www.rancher.com/
CattleWorks®	Cattle	Virginia	Mobilr or desktop	Livestock tracking, performance analytics, and customizable reports for cattle operations.	https://cattleworks.com/
AgriWebb	Cattle, buffalo, sheep and goat	Australia	software	livestock tracking, pasture monitoring, and data-driven insights to improve decision-making on the farm.	https://www.agriwebb.com/
Livestocked	cattle, sheep, goats etc.	United States	Website	Livestock record keeping, performance tracking, and herd management	https://livestocked.com/
CattleSoft	Cattle		Software platform	Cattle farming, including inventory management, breeding, health, and financial tracking	https://www.cattlesoft.com/
Cattle Krush	Cattle		Mobile friendly platform	Cattle inventory, health tracking, and financial management.	https://cattlekrush.com/login
PastureMap	Cattle, buffalo		Web based tool	Pasture planning and monitoring	https://www.pasturemap.com/
Farmbrite	Buffalo, cattle, sheep, goat etc	Hygiene	Software platform	Crop and livestock management, tracking feed and land use for buffalo	https://www.farmbrite.com/
Bushelfarm	Buffalo	United States	Software	Farm management, crop planning, tracking feed and land use for buffalo.	https://bushelfarm.com/
FarmOS	Buffalo	Open-source project	Web based	Farm management and record keeping	https://farmos.org/
Shearwell Data (sheep and cattle Tags)	Cattle, sheep and goats	USA	Pocket Size Shearwell X6 STOCK RECORDER	Livestock identification, Electronic Identification (EID) tags, and data management	https://www.shearwell.com/
FlockFiler	Sheep		Computer database	flock and herd managemen, and breeding records of sheep.	https://www.flockfiler.com/
Goatzz	Cattle, sheep, goats etc.	United States	Openherd website	An online marketplace for livestock, it connects buyers and sellers.	https://www.openherd.com/animals/goats/for-sale
GoatClassifieds	Goats		Online platform	Online classifieds platform for buying and selling goats, including details such as breed, age, gender, and pricing for each listing	http://ww38.goatclassifieds.com/
SmartShepherd	Sheep	Australia	Online platform	Increase lamb survival and monitor and manage the nutritional needs of livestock.	https://www.smartshepherd.com.au/

Livestock Behaviour Patterns: A deeper understanding of the interactions between livestock and their environment and how these dynamics influence behavior is fundamental to promoting animal welfare, productivity, and health. Behavioral changes often serve as the earliest indicators of potential illness, injury, or environmental discomfort. Therefore, accurately identifying and quantifying such behavioral shifts is vital for effective monitoring and decision-making in precision livestock systems (Tscharke and Banhazi, 2016; Rodriguez-Baena *et al.,* 2020). With the integration of artificial intelligence (AI), computer vision (CV), and sensor-based tools, behaviors such as eating, drinking, lameness, mounting, posture, tail-biting, and nursing can now be accurately identified in livestock. These innovations enable real-time, data-driven insights, improving welfare assessment and farm management efficiency (Bezen *et al.,* 2020; Chen *et al.,* 2021; Giovanini and Rufiner, 2023). Shin *et al.,* 2025, developed RT-DETR-based smart livestock monitoring enhances real-time cattle behavior (lesions and inactivity) detection accuracy and efficiency, outperforming YOLO models for intelligent farm management.

Similarly, activity and movement behaviors, including walking, running, and resting, have been successfully classified in cattle using deep learning architectures such as CNNs, Long Short-Term Memory (LSTM) networks, and XGBoost-based classifiers, achieving overall accuracies up to 97% (Gao *et al.,* 2023). Social interaction behaviors, including aggression, dominance hierarchy, and grouping, have been recognized through spatio-temporal deep learning models capable of hierarchical detection (Fuentes *et al.,* 2020). Furthermore, sensor-based technologies have facilitated the monitoring of reproductive behaviors, supporting the identification of robust cattle breeds with enhanced adaptability and stress resilience (Neethirajan, 2020). Likewise, resting and sleeping behaviors have been effectively detected using collar-mounted triaxial accelerometer sensors analyzed through LSTM algorithms, where 1-minute serial acceleration signals segmented within 4-minute windows yielded highly accurate detection of resting and eating behaviors (Nogoy *et al.,* 2022) (Table 3). Fig. 8 illustrates a generalized framework for detecting livestock behaviors using deep learning (DL) techniques. For example, computer vision and image analysis are particularly effective for detecting feeding, movement, and social interactions by analyzing video or image data. Sensor-based methods, such as accelerometers, are suitable for reproductive behaviors and resting detection by capturing motion or physiological signals. Time-series DL models like LSTM and RNN can be applied to sequential data from sensors or video-derived features to identify temporal patterns in activity and rest. This framework highlights how combining multiple DL approaches enables comprehensive monitoring of livestock behavior, supporting welfare assessment, disease detection, and management decisions.

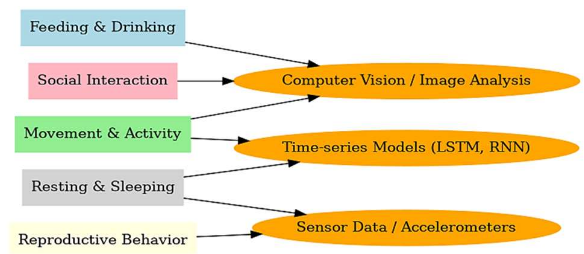

Fig. 8: Conceptual overview of livestock behavior categories and their detection using deep learning (DL) methods.

Individual Animal Identification and Breed Classification: Breed identification of livestock animals can be significantly enhanced through the integration of AI-based technology with advanced genetic analysis techniques. AI-powered computational methods can process vast amounts of genomic data with unprecedented speed and accuracy, enabling rapid and precise identification of animal breeds. The identification and detection of various cattle breeds, including Afrikaner, Brown Swiss, Holstein Friesian, Gir, Limousin, White Park, Marchigiana, and Simmental, have been facilitated by computer vision-based approaches utilizing deep learning techniques. The RTDETR-Refa algorithm enhances cattle breed identification accuracy (91.6%) using an improved ResNet18 architecture with Faster-Block and Efficient Multiscale Attention modules (Li *et al.,* 2025b). Kumar *et al.,* (2025) proposed a cross-attention encoder with pairwise triplet loss that efficiently integrates facial and muzzle features, achieving 93.67% accuracy with only 0.6 million parameters. Gupta *et al.,* (2022) employed YOLOv4 for breed identification based on size

Table 3: Overview of livestock behavior categories and corresponding AI-based recognition approaches

Behavior Category	Species	Algorithms	Insights	References
Recognizing the behavior (Eating, Drinking, lameness, mounting, posture, tail-biting, and nursing)	Pig, cattle, sheep	Computer Vision, Pattern Recognition, deep learning, image segmentation, and identification	Demonstrated the evolution from conventional image-based recognition to deep learning for accurate detection and analysis of multiple behavioral traits.	(Bezen *et al.*, 2020); Chen *et al.*, 2021; Giovanini, and Rufiner, 2023)
Feeding, Lying	Cattle	Bidir-LSTM	Achieved accuracy up to ~94.9%	(Wu *et al.*, 2022)
Social Interaction (Aggression, Hierarchy, Grouping)	Cattle	Deep learning with spatio-temporal modeling	Developed hierarchical recognition of social interactions using temporal and spatial deep learning features.	(Fuentes *et al.*, 2020)
Reproductive Behavior	Cattle	Sensor-based monitoring	Enabled real-time tracking of estrus and reproductive cycles; identification of resilient and stress-adapted breeds.	(Neethirajan, 2020)
Resting and sleeping	Cattle	Collar-mounted triaxial accelerometer sensor with LSTM	Demonstrated that LSTM models using 1-min serial acceleration signals (within 4-min windows) accurately detected resting and eating behaviors.	(Nogoy *et al.*, 2022)
Atypical lying down and standing up behaviors	Cattle	Accelerometers and machine learning	Machine learning and accelerometer data can objectively detect atypical cow behaviors, improving welfare assessment and housing design evaluation accuracy.	(Brouwers *et al.*, 2023)
Predicting Stress (Heat)	Cattle	Logistic regression and random forest	Machine learning models accurately predict dairy cow heat stress severity, enabling early detection and management to reduce milk loss and improve welfare.	(Becker *et al.*, 2021)
Forecast cattle heat stress.	Cattle	Deep learning framework (LSTM) and applied traditional statistical	Deep learning models using behavioural and meteorological data accurately forecast cattle heat stress.	(Chapman *et al.*, 2023)

and color, while Manoj *et al*. (2021) utilized CNNs) for the same purpose. Yılmaz *et al*. (2021) targeted specific regions on the cattle body using YOLOv4. Individual identification methods have also been developed. Ahmad *et al*. (2023) explored muzzle pattern identification using YOLOv7, while Kusakunniran *et al.,* (2020) employed various feature extraction techniques such as CLAHE, BoHoG, and LBP. Furthermore, Zin *et al*., (2020a) addressed ear tag recognition using YOLO, while Bello *et al.,* (2020) utilized CNN, Deep Belief Network (DBN), and Stacked Denoising Autoencoder for nose recognition. Pattern identification, including cropped body regions and pole locations, was studied by Zin *et al*. (2018) using Deep Convolutional Neural Networks. Additionally, Mandal *et al.* (2020) focused on six breeds, Jakhrana, Sirohi, Barbari, Beetal, Black Bengal, and Jamunapari, using InceptGI and CNN for breed identification. These approaches collectively underscore the potential of computer vision and deep learning techniques in accurately identifying and distinguishing various cattle breeds, thereby facilitating efficient livestock management practices. Technology-based results for various breeds are summarized in Table 4.

Disease Identification: AI and ML have been increasingly applied across multiple livestock species for automated health monitoring and disease diagnosis (Fig.9). In cattle, diverse computational models have been implemented to address reproductive and health challenges. For instance, Grzesiak *et al.* (2010) applied Classification Functions (CF), Artificial Neural Networks (ANN), Logistic Regression (LR), and Multivariate Adaptive Regression Splines (MARS) for predicting insemination problems, improving breeding efficiency.

In lameness detection, a range of advanced ML and sensor-based systems have been used. Taneja *et al.* (2020) employed Random Forest and KNN algorithms, while Alsaaod *et al*. (2019) utilized image processing, accelerometer data, and ground force reaction mats to classify locomotion abnormalities. Deep learning techniques, including CNN and SVM, were explored by Zin *et al*. (2020b), and hybrid ML models combining SVM, AdaBoost, Decision Trees (DT), and Random Forests were reported by Myint *et al*. (2024). Additionally, Gertz *et al*. (2020) demonstrated the utility of Classification and Regression Tree (CART) and XGBoost algorithms for accurate gait analysis and classification. AI applications have also shown promise in detecting infectious and metabolic diseases. Vyas *et al.* (2019) used sensors integrated with neural network algorithms to identify both Foot and Mouth Disease (FMD) and mastitis in cattle. More recently, XGBoost (Krisnawijaya *et al.,* 2025) and deep CNN architectures such as MobileNet and NasNetMobile (Kwenda *et al*., 2025) have been employed for FMD classification. For mastitis diagnosis, Kalkan *et al.,* (2025) evaluated multiple ML classifiers, GaussianNB, Decision Tree, SVM, KNN, Random Forest, Logistic Regression, XGBoost, and LightGBM, while Pan *et al*. (2025) combined LR, SVM, and Feedforward Neural Networks (FNN) to enhance clinical mastitis detection accuracy.

Table 4: Overview of AI-based technologies applied for breed identification and individual recognition across different livestock species.

Breed	Task	Classification type	Technology	References/Study
Cow	Breed identification or detection	Afrikaner, Brown Swiss, Holstein Friesian, Gyr, Limousin, White Park, Marchigiana and Simmental cattle	YOLOv4	(Gupta *et al.,* 2022)
		Size and color	Convolutional Neural Network	(Manoj *et al.,* 2021)
		Specific regions on the body	YOLO v4	(Yılmaz *et al.,* 2021)
		Muzzle pattern	YOLO v7	(Ahmad *et al.,* 2023)
	Individual Animal Identification	Muzzle Patterns	CLAHE, BoHoG, and LBP	(Kusakunniran *et al.,* 2020)
		Face Recognition	Convolutional Neural Network	(Wang *et al.,* 2020)
		Ear Tag Recognition	YOLO	(Zin *et al.,* 2020a)
		Nose	CNN, Deep Belief Network (DBN) and Stacked Denoising Auto Encoder	(Bello *et al.,* 2020)
			CNN, SVM	(Achour *et al.,* 2020)
		Pattern identification: cropping body region, pole location	Deep Convolutional Neural Network	(Zin *et al.,* 2018)
Buffalo	Breed identification or detection	Neli-Ravi, Khundi, and Mix	CNN, SVM	(Pan *et al.,* 2022)
		African buffalo	Decision tree	(Panhalkar and Doye, 2022)
Sheep	Breed identification or detection	Four breeds: Marino, Poll Dorset, Suffolk, White Suffolk	Convolution Neural Network	(Dutta, 2021)
		Four breeds	InceptionV3 CNN model, kNN, SVM, and ANN classifiers	(Koklu *et al.,* 2022)
		Four types of Sheep breed images	ResNet50, VGG16, VGG19, InceptionV3	(Agrawal *et al.,* 2021)
		Classification of sheep: Marino, Suffolk, White Suffolk, and Poll Dorset sheep	Convolutional Neural Network, Resnet50 network, VGG16 network	(Bimantoro, and Emanuel, 2021)
	Individual Identification	Facial bio-metrics	Convolutional Neural Network, Bayesian optimization	(Salama *et al.,* 2019)
		Images	Convolutional Neural Network VGG network models	(Sun *et al.,* 2021)
		Biometric identification system based on facial images	R-CNN , ResNet50V2	(Hitelman *et al.,* 2022)
Goat	Breed identification or detection	Six breeds: Jakhrana, sirohi, barbari, beetal, Blackbengal and Jamunapri	InceptGI, CNN	(Mandal *et al.,* 2020)
	Individual Identification	face detection	YOLOV7	(Wang *et al.,* 2023)
		cashmere goats	Cycle-Consistent Adversarial Network (Cycle-GAN), CrossEntropy	(Shang *et al.,* 2023)

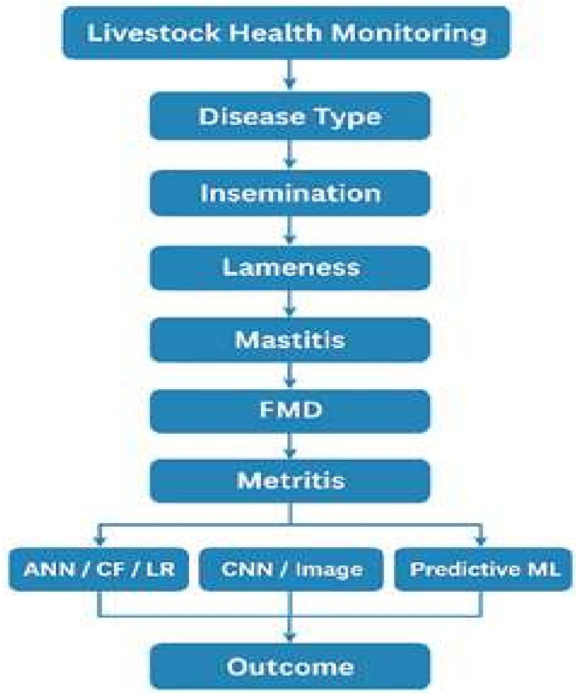

Fig. 9: Workflow for livestock health monitoring using AI method.

For uterine and hoof health issues, Džermeikaitė *et al.* (2025) developed ensemble ML models integrating Partial Least Squares Discriminant Analysis (PLS-DA), RF, SVM, and Neural Network (NN) approaches for early metritis detection. Similarly, Risvanli *et al.* (2024) employed an Iterative Classifier Optimizer algorithm for automated metritis identification. Magana *et al.* (2023) applied unsupervised learning (K-means) and the Tree-Based Pipeline Optimization Tool (TPOT) with sensor data for early prediction of digital dermatitis onset in dairy herds. Beyond cattle, small ruminants and buffaloes have also benefited from AI-assisted disease detection (Table 5).

Zhang *et al.* (2024) utilized ultrasound images of udders from 271 buffaloes and applied a deep learning model to detect mastitis, achieving an accuracy of 83%. In sheep, Barwick *et al.,* (2018) employed Quadratic Discriminant Analysis (QDA) for lameness classification, while Kaler *et al.* (2020) developed an accelerometer- and gyroscope-based ear sensor combined with Random Forest modeling for real-time mobility monitoring. Girmaw (2025) demonstrated deep-learning models such as EfficientNetB7, MobileNetV2, and DenseNet201 for detecting and classifying skin diseases across cattle, sheep, and goats, indicating strong potential for cross-species diagnostic frameworks.

Estrus, early pregnancy and calving detection: Accurate detection of estrus, early pregnancy, and calving events plays a critical role in optimizing reproductive efficiency and overall herd management. Various AI- and ML-based models have been developed to monitor these reproductive phases using behavioral, physiological, and environmental data. For estrus detection, Higaki *et al.* (2021) utilized three machine learning algorithms, Decision Tree, ANN, and SVM, to predict estrus behavior with improved accuracy. Similarly, Wang *et al.,* (2020) compared KNN, Back Propagation Neural Network (BPNN), Linear Discriminant Analysis (LDA), and CART models. Sasankar *et al,* (2023) combined Internet of Things (IoT) and machine learning to achieve real-time estrus prediction, while Yildiz *et al.* (2022) applied ANN models integrating mobility and environmental data. In early pregnancy detection, Ferraz *et al.* (2024) employed machine learning approaches for predictive modeling, while Marques *et al.* (2024) compared multiple algorithms, including Logistic Regression, Random Forest, LDA, SVM, AdaBoost (ADABAG), and Bagged Classification Tree (TREEBAG). Andrade *et al.*

Table 5: Summary of AI-based technologies applied for disease identification

Species	Classification type	Technology used	References
Cow	Insemination problem	Classification functions (CF), ANN, Logistic regression, and MARS	(Grzesiak *et al.,* 2010)
	Lameness detection	Random Forest, K-NN	(Taneja *et al.,* 2020)
		Image-processing techniques, Accelerometers, Ground force reaction, pressure-sensitive mat	(Alsaaod *et al.,* 2019)
		Deep neural network	(Ismail *et al.,* 2023)
		Machine learning algorithms, such as SVM, AdaBoost, DT, and Random Forests,	(Myint *et al.,* 2024)
		CART, XGBoost algorithm and Computing, Classification	(Gertz *et al.,* 2020)
	Foot and Mouth Disease (FMD) and Mastitis	Sensors, Machine Learning Algorithm (Neural Networks)	(Vyas *et al.,* 2019)
	Foot and Mouth Disease	XGBoost	(Krisnawijaya *et al.,* 2025)
	Foot and Mouth Disease	MobileNet and NasNetMobile	(Kwenda *et al.,* 2025)
	Mastitis diagnosis	GaussianNB, Decision Tree, Support Vector Machine, K-Nearest Neighbor, Random Forest, Logistic Regression, XGBoost and LightGBM algorithms.	(Kalkan *et al* ., 2025)
	Clinical Mastitis Detection	Integrating LR, SVM, and FNN	(Pan *et al.,* 2025)
	Early Detection of Metritis	Five classification models, PLS-DA, random forest (RF), SVM, NN, and an Ensemble model	(Džermeikaitė *et al.,* 2025)
	Metritis detection	Iterative Classifier Optimizer) algorithm	(Risvanli *et al.,* 2024)
	predict and detect early-onset of digital dermatitis	K-means and Tree-Based Pipeline Optimization Tool (TPOT), sensor	(Magana *et al.,* 2023)
Cattle, sheep, and goats	Skin disease detection and classification	Deep-learning models (EfficentNetB7, MobileNetV2, and DenseNet201)	(Girmaw, 2025)
Buffalo	Detect Mastitis	Deep Learning Network (EfficientNet_b3)	(Zhang *et al.,* 2024)
Sheep	Lameness	Accelerometer- and gyroscope-based ear sensor, random forest	(Kaler *et al.,* 2020)

(2023) further demonstrated the potential of deep learning by evaluating CNN architectures such as ResNet50, ResNeXt50, InceptionResNetV2, and DenseNet121 for early pregnancy prediction in cattle. For calving time prediction in cattle, deep learning models such as YOLOv8 (Mg *et al.,* 2025), CNN-LSTM, and CNN-BiLSTM-Attention frameworks (Yang *et al.,* 2024) have been successfully employed. Khin *et al.* (2024) also combined Mask R-CNN (Detectron2) and YOLOv8 for visual-based calving detection. Additionally, Kalkan *et al.* (2025) applied machine learning algorithms including Naïve Bayes, Random Forest, Decision Tree, and Logistic Regression to predict calving difficulty with high accuracy (Table 6).

Table 6: Summary of AI- and ML-based approaches for estrus, early pregnancy, and calving detection in livestock.

Classification type	Technology used	References
Estrus detection (cattle)	Three machine learning algorithms (decision tree, artificial neural network, and SVM)	(Higaki *et al.,* 2021)
	Four machine-learning approaches were tested KNN, back-propagation neural network (BPNN), linear discriminant analysis (LDA), and CART	(Wang *et al.,* 2020)
	Machine Learning and IoT	(Sasankar *et al.,* 2023)
	Artificial Neural Networks Using Mobility and Environmental Data	(Yildiz and Özgüven 2022)
Early pregnancy (cattle)	Machine learning models	(Ferraz *et al.,* 2024)
	Logistic regression, RF, LDA, SVM, Bagged AdaBoost (ADABAG), and TREEBAG.	(Marques *et al.,* 2024)
	Four CNN architectures were evaluated, namely ResNet50, ResNeXt50, InceptionResNetV2, and DenseNet121.	(Andrade *et al.,* 2023)
Calving time prediction (cattle)	YOLOv8 model	(Mg *et al.,* 2025)
	CNN, LSTM, CNN-LSTM, and CNN based bidirectional long short-term attention (CNN-BiLSTM-attention) models	(Yang *et al.,* 2024)
	Mask R-CNN from the Detectron2 detection and the YOLOv8	(Khin *et al.,* 2024)
Predict calving difficulty (cattle)	ML algorithms, namely naïve Bayes, random forest, decision trees, and logistic regression	(Kalkan *et al* ., 2025)

DISCUSSION

This review distinguishes itself by providing a comprehensive, integrated analysis of Precision Livestock Management through the combined lens of Artificial Intelligence, Computer Vision, and Sensor Technologies. Unlike previous reviews that typically focus on single technologies such as AI for disease detection (Menezes *et al.,* 2025), CV for behavior monitoring (Pesenti Rossi *et al.,* 2024), or sensor-based environmental monitoring (Yin *et al.,* 2023) this work synthesizes these domains into a unified framework, highlighting the synergistic benefits of integration in advancing animal welfare, productivity, and sustainability.

The convergence of AI, sensors, and CV has driven substantial progress in livestock health monitoring and management. Fusion technologies that combine video and sensor data enable early detection of diseases such as mastitis, lameness, and infectious illnesses, often identifying subtle physiological and behavioral changes before clinical symptoms appear. Similarly, image-based breed identification systems using advanced feature extraction and classification models have improved traceability and selective breeding outcomes, providing greater reliability than traditional tagging methods (Curti *et al.,* 2023; Menezes *et al.,* 2024; Singh *et al.,* 2025). Modern software platforms further strengthen livestock supervision by integrating AI algorithms with edge and cloud computing, delivering real-time diagnostics, event alerts, and monitoring dashboards accessible via mobile devices. Their modular and scalable designs make them adaptable to diverse species and farm sizes, enhancing practicality for both large-scale and smallholder operations (Singh *et al.,* 2025). Behavioral pattern recognition through AI and CV has emerged as a powerful tool for welfare assessment. Changes in feeding, locomotion, and social interaction patterns strongly correlate with early disease onset and welfare indicators. Standardized behavioral libraries across species could improve the generalizability of predictive models, enabling more robust decision-making (de Freitas Curti *et al.,* 2023; Menezes *et al.,* 2024). A critical consideration in applying AI to livestock management is the choice of analytical approach. Traditional machine learning methods such as support vector machines and random forests are computationally efficient, less data-intensive, and interpretable, making them suitable for smallholder contexts. However, they rely on manual feature engineering and may miss complex patterns in multimodal data. Deep learning approaches, including convolutional and recurrent neural networks and transformer-based models, automatically extract high-level features and demonstrate superior performance in tasks such as disease detection, pose estimation, and behavior recognition. Yet, they require large annotated datasets, substantial computational resources, and remain difficult to interpret. Fig. 10 illustrates the trade-off between ML simplicity and interpretability versus DL accuracy and scalability, guiding hybrid or context-aware model selection strategies tailored to specific livestock production systems.

Despite these advancements, several challenges remain. Integrating heterogeneous data streams from sensors and CV requires robust frameworks for synchronization, storage, and interpretation. The variability of behavior and physiology across breeds and environments highlights the need for context-aware AI models. Cost remains a critical barrier: high-resolution cameras, sensors, and cloud infrastructure are expensive, and many platforms target industrial-scale farms, limiting accessibility for smallholders. Ethical considerations, including data ownership, privacy, algorithmic bias, animal welfare, and equitable access, must be addressed to ensure responsible adoption (Distante *et al.,* 2025; Singh *et al.,* 2025). Recent advances demonstrate that AI-driven video monitoring can also be cost-effective. For instance, RGB camera-based systems integrating YOLOv8 for object detection, VGG for feature extraction, and SVM for final identification facilitate robust automatic identification of individual cattle, reducing labor costs while ensuring high accuracy (Mon *et al.,* 2024). Understanding adoption barriers is equally important. Explainable AI (XAI) approaches applied to assess technological readiness in Precision Livestock Farming reveal key factors influencing farmer adoption, supporting targeted technology design and business strategies (Mallinger *et al.,* 2024). Finally, ethical considerations remain central to the responsible implementation of PLM. AI systems must avoid objectifying animals, respect their welfare, ensure farmer data rights, and maintain human oversight to mitigate potential misuse, algorithmic bias, and unequal access among smallholders (Omotayo *et al.,* 2025).

Therefore, the fusion of AI, CV, and ST is transforming livestock management by enabling precise disease detection, reliable breed identification, and continuous welfare monitoring. Future research should prioritize overcoming data integration challenges, reducing costs through scalable solutions, and developing inclusive, species-specific AI models. Establishing standardized behavioral databases and ethical guidelines will enhance the applicability and trustworthiness of these technologies, ensuring that PLM innovations translate into practical, sustainable benefits for global livestock farming.

Limitations, Challenges, and Future Perspectives: Since its introduction by John McCarthy in 1956, Artificial Intelligence has steadily advanced applications in poultry, dairy, and pig farming, enhancing efficiency, sustainability, and productivity. AI supports data-driven decision-making, reduces resource dependency, and minimizes human error, with applications in animal identification, welfare assessment, disease detection, and feed management. Emerging technologies such as drones, robotics, and blockchain further strengthen farm automation, though high implementation costs, data infrastructure needs, and workforce adaptation remain major barriers (Melak *et al.,* 2024). Despite its promise, the integration of AI, CV, and sensor-based systems in livestock farming faces several technical and operational challenges. These include limited standardized datasets, poor model generalization across breeds and environments, inadequate connectivity in rural areas, and a shortage of skilled personnel. Real-time data integration from multimodal sensors, wearable, environmental, and imaging, demands strong computational resources and advanced algorithmic design. Moreover, maintenance costs, data security, and ethical concerns related to automated surveillance and animal welfare present long-term sustainability issues (Curti *et al.,* 2023; Neethirajan, 2024).

To address these limitations, future research should prioritize:

- Standardized, open-access datasets to enable benchmarking and cross-study validation.
- Development of interpretable and lightweight AI models that perform robustly under variable farm conditions.
- Integration of AI with IoT, blockchain, and genomic tools for comprehensive and traceable livestock management.
- Adoption of edge computing and on-device analytics to reduce latency and dependence on high-end infrastructure.
- Ethical frameworks and participatory design approaches to ensure transparency, fairness, and social acceptance among farmers.

AI-driven Precision Livestock Farming (PLF) holds transformative potential for real-time monitoring of animal health, behavior, reproduction, and nutrition. Achieving scalable, explainable, and cost-effective AI systems through cross-disciplinary collaboration between researchers, policymakers, and industry stakeholders will be essential to translating laboratory advances into practical, sustainable livestock management (Antognoli *et al.,* 2025; Shin *et al.,* 2025).

Conclusions: In essence, precision livestock management epitomizes the pivotal roles of AI, computer vision, and sensor technologies in advancing sustainable agriculture while prioritizing animal welfare. These cutting-edge tools enable farmers to tailor care strategies to individual animals, surpassing conventional methods through real-time monitoring and proactive health management. This approach not only enhances animal well-being and productivity but also aligns with global demands for ethical and environmentally conscious farming. Looking ahead, practical industry adoption requires the development of affordable, user-friendly AI solutions accessible to farms of all scales. Future research should prioritize optimizing AI algorithms for diverse livestock types and environmental conditions, addressing ethical concerns such as data privacy and animal welfare, and conducting long-term field studies to evaluate economic and social impacts. The integration of these technologies promises a transformative, intelligent, and humane approach to livestock management that drives both economic viability and ecological sustainability.

Future Directions: While significant progress has been made in applying deep learning for cattle identification and breed classification, the field still lacks practical translation from research to farm-level implementation. Future research should prioritize the development of robust, lightweight, and interpretable models that can perform reliably in dynamic farm environments with variable lighting, poses, and backgrounds. Creating standardized, multi-breed datasets with open access will enable fair benchmarking and accelerate innovation.

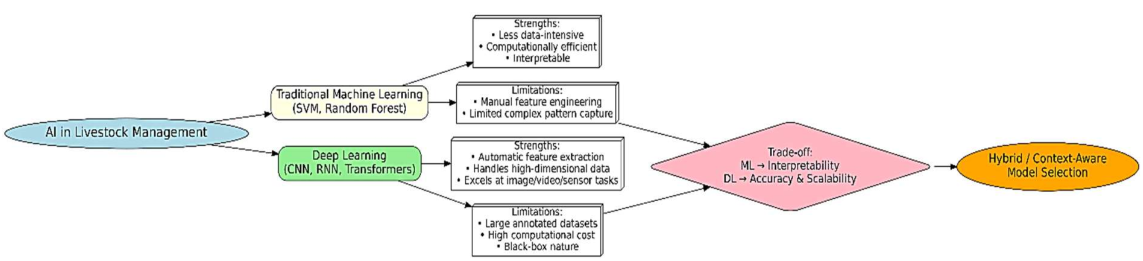

Fig. 10: Conceptual framework comparing traditional machine learning and deep learning approaches in livestock management.

Future Directions: While significant progress has been made in applying deep learning for cattle identification and breed classification, the field still lacks practical translation from research to farm-level implementation. Future research should prioritize the development of robust, lightweight, and interpretable models that can perform reliably in dynamic farm environments with variable lighting, poses, and backgrounds. Creating standardized, multi-breed datasets with open access will enable fair benchmarking and accelerate innovation.

For industry stakeholders, the focus should shift toward deploying scalable, cost-effective solutions that integrate seamlessly with existing livestock management systems. Real-time, on-device analytics and easy-to-use interfaces will be key for field adoption. For researchers, attention should be given to model explainability, cross-environment validation, and ethical data use to ensure transparency and trust. Strong collaboration between academia, AI developers, and the livestock industry will be essential to transform algorithmic progress into practical tools that enhance traceability, productivity, and animal welfare in modern livestock systems.

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REFERENCES

Abbadi MA, Al-Bustanji AM and Al-kasassbeh M, 2020. Robust intelligent malware detection using light GBM algorithm. International Journal of Innovative Technology and Exploring Engineering 9(6):1253-1260.

Achour B, Belkadi M, Filali I, *et al.,* 2020. Image analysis for individual identification and feeding behaviour monitoring of dairy cows based on Convolutional Neural Networks (CNN). Biosystems Engineering 198:31-49.

Agrawal D, Minocha S, Namasudra S, *et al.,* 2021. Ensemble Algorithm using Transfer Learning for Sheep Breed Classification. IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania, pp: 199-204, doi: 10.1109/SACI51354.2021.9465609.

Ahmad M, Abbas S, Fatima A, *et al.,* 2023. AI-Driven livestock identification and insurance management system. Egyptian Informatics Journal 24(3):100390.

Alsaaod M, Fadul M and Steiner A, 2019. Automatic lameness detection in cattle. Veterinary Journal 246: 35-44.

Andrade AC, da Silva LO, Souza VF, *et al.*, 2023. Identifying pregnancy in cows using ovarian ultrasound images and convolutional neural networks-a proof-of-concept study. Computers and Electronics in Agriculture 206:107674.

Antognoli V, Presutti L, Bovo M, *et al.,* 2025. Computer vision in dairy farm management: A literature review of current applications and future perspectives. Animals 15(17):2508.

Balderas AJ, Pangilinan KMA and Caya MVC, 2025. You only look once v8 cattle identification based on muzzle print pattern using ORB and fast library for approximate nearest neighbor algorithms. Engineering Proceedings 92(1): 53.

Banhazi TM, Babinszky L, Halas V, *et al.,* 2012. Precision Livestock Farming: Precision feeding technologies and sustainable livestock production. International Journal of Agricultural and Biological Engineering 5(4):54-61.

Becker CA, Aghalari A, Marufuzzaman M, *et al.,* 2021. Predicting dairy cattle heat stress using machine learning techniques. Journal of Dairy Science 104(1):501-524.

Bello RW, Talib AZH and Mohamed ASAB, 2020. Deep learning-based architectures for recognition of cow using cow nose image pattern. Gazi University Journal of Science 33(3):831-844.

Berckmans D, 2017. General introduction to precision livestock farming. Animal Frontiers 7(1):6-11.

Bezen R, Edan Y and Halachmi I, 2020. Computer vision system for measuring individual cow feed intake using RGB-D camera and deep learning algorithms. Computers and Electronics in Agriculture 172:105345.

Bimantoro MZ and Emanuel AWR, 2021. Sheep Face Classification using Convolutional Neural Network. 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT), Surabaya, Indonesia, pp:111-115, doi: 10.1109/EIConCIT50028.2021.9431933.

Brouwers SP, Simmler M, Savary P, *et al.,* 2023. Towards a novel method for detecting atypical lying down and standing up behaviors in dairy cows using accelerometers and machine learning. Smart Agricultural Technology 4:100199.

Chapman NH, Chlingaryan A, Thomson PC, *et al.,* 2023. A deep learning model to forecast cattle heat stress. Computers and Electronics in Agriculture 211:107932.

Chaudhry AA, Mumtaz R, Zaidi SMH, *et al.,* 2020. Internet of Things (IoT) and machine learning (ML) enabled livestock monitoring. In *2020 IEEE 17th international conference on smart communities: improving quality of life using ICT, IoT and AI (HONET),* pp: 151-155. IEEE.

Chen C, Zhu W and Norton T, 2021. Behaviour recognition of pigs and cattle: Journey from computer vision to deep learning. Computers and Electronics in Agriculture 187:106255.

Curti P D F, Selli A, Pinto D L, *et al.*, 2023. Applications of livestock monitoring devices and machine learning algorithms in animal production and reproduction: an overview. Animal Reproduction 20(2): e20230077.

Dao VN and Vemuri VR, 2002. A performance comparison of different back propagation neural networks methods in computer network intrusion detection. Differential equations and dynamical systems 10(1&2), 201-214.

Das SK, 2018. Impact of climate change (heat stress) on livestock: adaptation and mitigation strategies for sustainable production. Agriculture Reviews 39 (2):130-136.

Dawkins MS, 2025. Smart farming and Artificial Intelligence (AI): How can we ensure that animal welfare is a priority? Applied Animal Behaviour Science 283:106519.

Deng L and Yu D, 2014. Deep learning: methods and applications. Foundations and Trends& in Signal Processing 7(3-4):197-387.

Ding L, Zhang C, Yue Y, *et al.*, 2025. Wearable sensors-based intelligent sensing and application of animal behaviors: A comprehensive review. Sensors 25(14):4515.

Distante D, Albanello C, Zaffar H, *et al.,* 2025. Artificial intelligence applied to precision livestock farming: A tertiary study. Smart Agricultural Technology 11:100889

Dutta P, 2021. A deep learning approach for animal breed classification-sheep. International Journal for Research in Applied Science Engineering Technology 9(5):10-22214.

Džermeikaitė K, Krištolaitytė J and Antanaitis R, 2025. Application of machine learning models for the early detection of metritis in dairy cows based on physiological, behavioural and milk quality indicators. Animals 15(11):1674.

Egon K and Oloyede J O, 2023. Advancements in Sensor Technologies for Precision Livestock Farming. Available online: https://osf.io/preprints/osf/av68m (accessed on 23 December 2025)

Famuyiwa AS, Dosunmu OP and Jimi-Olatunji D, 2024. Application of computer-based techniques for monitoring animal health, behavior and welfare: A review. Journal of Applied Sciences and Environmental Management 28(12B Supplementary): 4277-4282.

Faye BM, Diop F and Niang I, 2025. Edge-AI and IoT Based Smart Agriculture: Challenges and Use Cases. In *International Conference on Africa Data, AI and Innovations*, pp: 94-104). Cham: Springer Nature Switzerland.

Feng J and Yi C, 2022. Lightweight detection network for arbitrary-oriented vehicles in UAV imagery via global attentive relation and multi-path fusion. Drones 6(5):108.

Fernandes AFA, Dórea JRR and Rosa GJDM, 2020. Image analysis and computer vision applications in animal sciences: an overview. Frontiers in Veterinary Science 7:551269.

Ferraz PA, Poit DAS, Pinto LMF, *et al.,* 2024. Accuracy of early pregnancy diagnosis and determining pregnancy loss using different biomarkers and machine learning applications in dairy cattle. Theriogenology 224:82-93.

Foley JA, Ramankutty N, Brauman KA, *et al*., 2011. Solutions for a cultivated planet. Nature, 478(7369):337-342

Fuentes A, Yoon S, Park J, *et al.,* 2020. Deep learning-based hierarchical cattle behavior recognition with spatio-temporal information. Computers and Electronics in Agriculture 177:105627.

Fuentes S, Viejo CG, Tongson E, *et al.,* 2022. The livestock farming digital transformation: implementation of new and emerging technologies using artificial intelligence. Animal Health Research Reviews 23(1):59-71.

Gao G, Wang C, Wang J, *et al*., 2023. CNN-Bi-LSTM: A complex environment-oriented cattle behavior classification network based on the fusion of CNN and Bi-LSTM. Sensors 23(18):7714.

Gerber PJ, Steinfeld H, Henderson B, *et al*., 2013. Tackling climate change through livestock: a global assessment of emissions and mitigation opportunities. pp: xxi+-115. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. http://www.fao.org/docrep/018/i3437e/i3437e00.htm

Gertz M, Grobe-Butenuth K, Junge W, *et al.,* 2020. Using the XGBoost algorithm to classify neck and leg activity sensor data using on-farm health recordings for locomotor-associated diseases. Computers and Electronics in Agriculture 173:105404.

Giovanini L and Rufiner H, 2023. Information Technologies in Feeding Behavior Livestock Monitoring. *In: Zhang Q.* (*eds*) Encyclopedia of Digital Agricultural Technologies. Springer, Cham. https://doi.org/10.1007/978-3-031-24861-0_247

Girshick R, 2015. Fast R-CNN. In Proceedings of the IEEE international conference on computer vision, Santiago, Chile pp:1440-1448

Girmaw DW, 2025. Livestock animal skin disease detection and classification using deep learning approaches. Biomed Signal Process Control 102:107334.

Gjergji M, de Moraes Weber V, Silva LOC, *et al.,* 2020. Deep Learning Techniques for Beef Cattle Body Weight Prediction. International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 2020, pp:1-8, doi: 10.1109/IJCNN48605.2020.9207624.

Grace GH, Martin N, and Pradeepa I, *et al.,* 2024. Classification of Livestock Diseases Using Machine Learning Algorithms. In How Machine Learning is Innovating Today's World (eds A. Dey, S. Nayak, R. Kumar and S.N. Mohanty). 127-138 https://doi.org/10.1002/9781394214167.ch10

Grzesiak W, Zaborski D, Sablik P, *et al.,* 2010. Detection of cows with insemination problems using selected classification models. Computers and Electronics in Agriculture 74(2):265-273.

Guarnido-Lopez P, Pi Y, Tao J, *et al.,* 2024. Computer vision algorithms to help decision-making in cattle production. Animal Frontiers 14(6):11-22.

Gupta H, Jindal P, Verma OP, *et al.,* 2022. Computer vision-based approach for automatic detection of dairy cow breed. Electronics 11(22):3791.

Gupta RK, Lathwal SS, Mohanty TK, *et al.,* 2014. Detection of lameness of cow based on body weight using artificial neural network. International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, pp: 337-341, doi: 10.1109/IndiaCom.2014.6828155.

Gupta S, 2024. AI Applications in Animal Behavior Analysis and Welfare. In *Agriculture 4.0*, pp: 224-244). CRC Press.

Halachmi I and Guarino M, 2016. Precision livestock farming: a 'per animal'approach using advanced monitoring technologies. Animal 10(9):1482-1483.

Halachmi I, Guarino M, Bewley J *et al.,* 2019. Smart animal agriculture: application of real-time sensors to improve animal well-being and production. Annual Review of Animal Biosciences 7(1):403-425.

Higaki S, Okada H, Suzuki C, *et al.,* 2021. Estrus detection in tie-stall housed cows through supervised machine learning using a multimodal tail-attached device. Computers and Electronics in Agriculture 191:106513.

Hitelman A, Edan Y, Godo A, *et al.,* 2022. Biometric identification of sheep via a machine-vision system. Computers and Electronics in Agriculture 194:106713.

Ibraheam M, Li KF, Gebali F, *et al*., 2021. A performance comparison and enhancement of animal species detection in images with various R-CNN models. AI, 2(4):552-577.

Ismail S, Diaz M & Ferrer MA, 2025. Deep learning for lameness level detection in dairy cows. Engineering Applications of Artificial Intelligence 151:110611.

Iwasaki W, Morita N and Nagata MPB, 2019. IoT sensors for smart livestock management. In *Chemical, gas, and biosensors for internet of things and related applications*, pp:207-221). Elsevier. ISBN 9780128154090

Kaler J, Mitsch J, Vázquez-Diosdado JA, *et al.,* 2020. Automated detection of lameness in sheep using machine learning approaches: novel insights into behavioural differences among lame and non-lame sheep. Royal Society Open Science 7(1):190824.

Kalkan A, Tepeli M, and Göde A, 2025. Mastitis diagnosis with machine learning algorithms. Neural Computing & Applications 37(18):12351-12372.

Kamilaris A and Prenafeta-Boldú FX, 2018a. A review of the use of convolutional neural networks in agriculture. The Journal of Agricultural Science 156(3):312-322.

Kamilaris A and Prenafeta-Boldú FX, 2018b. Deep learning in agriculture: A survey. Computers and Electronics in Agriculture 147:70-90.

Kang X, Zhang XD and Liu G, 2021. A review: development of computer vision-based lameness detection for dairy cows and discussion of the practical applications. *Sensors* 21(3):753.

Karunathilake EMBM, Le AT, Heo S, *et al.,* 2023. The path to smart farming: Innovations and opportunities in precision agriculture. Agriculture 13(8):1593.

Kaveh M and Mesgari MS, 2023. Application of meta-heuristic algorithms for training neural networks and deep learning architectures: A comprehensive review. Neural Processing Letters 55(4):4519-4622.

Khin MP, Tin P, Horii Y, *et al.,* 2024. Predictive modeling of cattle calving time emphasizing abnormal and normal cases by using posture analysis. Scientific Reports 14(1), 31871.

Koklu M, Cinar I, Taspinar YS, *et al.,* 2022. Identification of Sheep Breeds by CNN- Based Pre-Trained Inceptionv3 Model. 11th Mediterranean Conference on Embedded Computing (MECO), Budva, Montenegro, pp: 01-04, doi: 10.1109/MECO55406.2022.9797214.

Krisnawijaya NNK, Catal C, Tekinerdogan B, *et al.,* 2025. A machine learning approach to identifying foot and mouth disease incidence in Dairy Farms with suboptimal veterinary infrastructure. Smart Agricultural Technology 12:101261.

Kumar N, Sharma A, Kumar A, *et al.,* 2025. Cattle verification with YOLO and cross-attention encoder-based pairwise triplet loss. Computers and Electronics in Agriculture 234:110223.

Kumar VS, Kumar RP, Harikrishna CH, *et al.,* 2018. Effect of heat stress on production and reproduction performance of buffaloes-A review. Pharma Innovation Journal 7(4): 629-633.

Kusakunniran W, Wiratsudakul A, Chuachan U, *et al.,* 2018. Automatic cattle identification based on fusion of texture features extracted from muzzle images. IEEE International Conference on Industrial Technology (ICIT), Lyon, France, pp: 1484-1489, doi: 10.1109/ICIT.2018.8352400.

Kwenda C, Bakasa W, Simbula R, *et al.,* 2025. Mobile Diagnosis of Foot and Mouth Disease in Cattle Based on Hybrid Deep Neural Networks. In *2025 Conference on Information Communications Technology and Society (ICTAS)*, pp:1-7. IEEE.

Landim NMD, Dias BS, Santos CAD, *et al.,* 2024. The Use of Artificial Intelligence in Automated Estrous Detection. In *2024 IEEE International Conference on Microwaves, Communications, Antennas, Biomedical Engineering and Electronic Systems (COMCAS)*, pp: 1-4). IEEE.

Li T, Ruirui Z, Zhao H, *et al*., 2025a. Advancements in Intelligent Monitoring Technologies for Behavioral, Physiological, and Biomarker Analysis in Cattle Health: A Review. Agriculture 16(1):39.

Li B, Fang J and Zhao Y, 2025b. RTDETR-Refa: a real-time detection method for multi-breed classification of cattle. Journal of Real-Time Image Processing 22(1): 38.

Magana J, Gavojdian D, Menahem Y, *et al.,* 2023. Machine learning approaches to predict and detect early-onset of digital dermatitis in dairy cows using sensor data. Frontiers in Veterinary Science10: 1295430.

Mahmud MS, Zahid A, Das AK, *et al*., 2021. A systematic literature review on deep learning applications for precision cattle farming. Computers and Electronics in Agriculture 187: 106313.

Mallinger K, Corpaci L, Neubauer T, *et al.,* 2024. Breaking the barriers of technology adoption: Explainable AI for requirement analysis and technology design in smart farming. Smart Agric Technol 9:100658.

Mandal SN, Ghosh P, Mukherjee K, *et al*., 2020. InceptGI: a ConvNet-Based classification model for identifying goat breeds in India. Journal of The Institution of Engineers (India): Series B 101(5):573-584.

Mansoor S, Karunathilake EM, Tuan TT, *et al.,* 2025. Genomics, phenomics, and machine learning in transforming plant research: advancements and challenges. Horticultural Plant Journal 11(2):486-503.

Marques TC, Marques LR, Fernandes PB, *et al.,* 2024. Machine learning to predict pregnancy in dairy cows: an approach integrating automated activity monitoring and on-farm data. Animals 14(11):1567.

Melak A, Aseged T and Shitaw T, 2024. The influence of artificial intelligence technology on the management of livestock farms. International Journal of Distributed Sensor Networks 2024(1): 8929748.

Menezes GL, Mazon G, Ferreira RE, *et al.,* 2024. Artificial intelligence for livestock: a narrative review of the applications of computer vision systems and large language models for animal farming. Animal Frontiers 14(6):42-53.

Mg WHE, Zin TT, Tin P, *et al.,* 2025. Automated system for calving time prediction and cattle classification utilizing trajectory data and movement features. Scientific Reports15(1): 2378.

Møller MF, 1993. A scaled conjugate gradient algorithm for fast supervised learning. Neural networks 6(4): 525-533.

Mon SL, Onizuka T, Tin P, *et al.,* 2024. AI-enhanced real-time cattle identification system through tracking across various environments. Scientific Reports 14(1):17779.

Morales EF and Escalante HJ, 2022. A brief introduction to supervised, unsupervised, and reinforcement learning. In Biosignal processing and classification using computational learning and intelligence, pp:111-129. Academic Press.

Myint BB, Onizuka T, Tin P, *et al.,* 2024. Development of a real-time cattle lameness detection system using a single side-view camera. Scientific Reports 14(1):13734.

Naoum RS, Abid NA & Al-Sultani ZN, 2012. An enhanced resilient backpropagation artificial neural network for intrusion detection system. International Journal of Computer Science and Network Security 12(3):11-17

Neethirajan S, 2024. Artificial intelligence and sensor innovations: enhancing livestock welfare with a human-centric approach. Human-Centric Intelligent Systems 4(1):77-92.

Neethirajan S, Reimert I and Kemp B, 2021. Measuring farm animal emotions—Sensor-based approaches. Sensors 21(2):553.

Nogoy KMC, Chon SI, Park JH, *et al.,* 2022. High precision classification of resting and eating behaviors of cattle by using a collar-fitted triaxial accelerometer sensor. Sensors 22(16):5961.

Omotayo AO, Adediran SA, Omotoso AB, *et al.,* 2025. Artificial intelligence in agriculture: ethics, impact possibilities, and pathways for policy. Computers and Electronics in Agriculture 239:110927.

Pan Y, Jin H, Gao J, *et al.,* 2022. Identification of Buffalo Breeds Using Self-Activated-Based Improved Convolutional Neural Networks. Agriculture 12(9):1386.

Pan L, Chen X, Han D, *et al.,* 2025. Machine learning-based clinical mastitis detection in dairy cows using milk electrical conductivity and somatic cell count. Frontiers in Veterinary Science 12:1671186.

Panhalkar AR and Doye DD, 2022. Optimization of decision trees using modified African buffalo algorithm. Journal of King Saud University Computer and Information Sciences 34(8):4763-4772.

Pawar J, Sonavale R and Sarkale MPS, 2024. Transforming Cattle Farming with Artificial Intelligence: Innovations, Applications, and Implications for Precision Livestock Management and Sustainable Agriculture Practices. REDVET-Revista electrónica de Veterinaria 25(1):525-537.

Pesenti Rossi G, Dalla Costa E, Barbieri S, *et al.,* 2024. A systematic review on the application of precision livestock farming technologies to detect lying, rest and sleep behavior in dairy calves. Frontiers in Veterinary Science 11:1477731

Psota ET, Luc EK, Pighetti GM, *et al*., 2021. Development and validation of a neural network for the automated detection of horn flies on cattle. Computers and Electronics in Agriculture, 180, 105927

Qiao Y, Guo Y and He D, 2023. Cattle body detection based on YOLOv5-ASFF for precision livestock farming. Computers and Electronics in Agriculture 204:107579.

Ranganathan A, 2004. The levenberg-marquardt algorithm. Tutoral on LM algorithm 11(1):101-110.

Ren K, Karlsson J, Liuska M, *et al.,* 2020. A sensor-fusion-system for tracking sheep location and behaviour. International Journal of Distributed Sensor Networks 16(5):1550147720921776.

Risvanli A, Tanyeri B, Yildirim G, *et al.,* 2024. Metrisor: A novel diagnostic method for metritis detection in cattle based on machine learning and sensors. Theriogenology 223:115-121.

Rodríguez Espinosa H, Bastidas Duque A and Naranjo Arroyave JE, 2016. Application of Geographic Information Systems (GIS) for the implementation of precision farming. Livestock Research for Rural Development 28(8):144, Retrieved February 13 2025: from http://www.lrrd.org/lrrd28/8/rodr28144.html

Rodriguez-Baena DS, Gomez-Vela FA, García-Torres M, *et al.,* 2020. Identifying livestock behavior patterns based on accelerometer dataset. Journal of Computational Science 41:101076.

Rojas-Downing MM, Nejadhashemi AP, Harrigan T, *et al.,* 2017. Climate change and livestock: Impacts, adaptation, and mitigation. Climate Risk Management 16:145-163.

Rutten CJ, Velthuis AGJ, Steeneveld W, *et al.,* 2013. Invited review: Sensors to support health management on dairy farms. Journal of Dairy Science 96(4):1928-1952.

Saida A, Ramchander A, Reddy BSB, *et al.,* 2025. AI-enhanced livestock health and disease prediction in dairy and poultry farms. In *Multi-Disciplinary Research and Sustainable Development,* pp:191-198. CRC Press.

Salama A, Hassanien AE and Fahmy A, 2019. Sheep identification using a hybrid deep learning and bayesian optimization approach. IEEE Access 7(3):1681-31687

Sanjeevi P, Prasanna S, Siva Kumar B, *et al.,* 2020. Precision agriculture and farming using Internet of Things based on wireless sensor network. Transactions on Emergerging Telecommunications Technologies 31(12): e3978.

Santos CAD, Landim NMD, Araújo HXD, *et al.,* 2022. Automated systems for estrous and calving detection in dairy cattle. AgriEngineering 4(2):475-482.

Sarini NP, and Dharmawan K, 2023. Estimation of bali cattle body weight based on morphological measurements by machine learning algorithms: random forest, support vector, K-Neighbors, and extra tree regression. Journal of Advanced Zoology 44(3):1-9

Sasankar P, Pande MS, Singh MP, *et al.,* 2023. Estrus Detection System in Dairy Cows' using Machine Learning and IoT. In *2023 11th International Conference on Emerging Trends in Engineering and Technology-Signal and Information Processing (ICETET-SIP),* pp: 1-5). IEEE.

Schmidt A, Mohareri O, DiMaio S, *et al*., 2024. Tracking and mapping in medical computer vision: A review. Medical Image Analysis, 94:103131.

Seo S, 2025. Precision feeding, precision livestock farming, SMART farming: are these our prospective livestock farming? Animal Industry and Technology 12(1):1-19.

Shafiee MJ, Chywl B, Li F, *et al*., 2017. Fast YOLO: A fast you only look once system for real-time embedded object detection in video. arXiv preprint arXiv:1709.05943.

Shang C, Zhao H, Wang M, *et al*., 2023. Individual identification of cashmere goats via method of fusion of multiple optimization. Computer Animation and Virtual Worlds, 34(2): e2048.

Shin M, Hwang S and Kim B, 2025. AI-Based Smart Monitoring Framework for Livestock Farms. Appl Sci 15(10): 5638.

Singh D, Singh R, Gehlot A, *et al.,* 2025. Sensor and Computer Vision Based Cattle Health Monitoring and Management. SSRG International Journal of Electrical and Electronics Engineering 12(1):94-103

Sun F, Wang H & Zhang J, 2021. A recognition method of cattle and sheep based on convolutional neural network. In 2021 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT), Shanghai, China. pp:420-424. IEEE.

Szeliski R, 2022. Computer vision: algorithms and applications. Springer Nature.

Taneja M, Byabazaire J and Jalodia N, 2020. Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle. Computers and Electronics in Agriculture 171:105286.

Tscharke M and Banhazi TM, 2016. A brief review of the application of machine vision in livestock behaviour analysis. Journal of Agricultural Informatics 7(1):23-42, https://doi.org/10.17700/jai.2016.7.1.279

Tzanidakis C, Tzamaloukas O, Simitzis P *et al.,* 2023. Precision livestock farming applications (PLF) for grazing animals. Agriculture 13(2): 288.

UN Environment Programme (2023) https://www.unep.org/news-and-stories/press-release/novel-meat-and-dairy-alternatives-could-help-curb-climate-harming (accessed on 18 February 2026).

United Nations (2021). https://www.un.org/en/desa/world-population-projected-reach-98-billion-2050-and-112-billion-2100 (accessed on 18 February 2026)

Valin H, Sands RD, Van der Mensbrugghe D, *et al*., 2014. The future of food demand: understanding differences in global economic models. Agricultural economics 45(1):51-67

van Erp-van der E and Rutter SM, 2020. Using precision farming to improve animal welfare. CABI Reviews 15(51):1-10, https://doi.org/10.1079/PAVSNNR202015051

Vyas S, Shukla V and Doshi N, 2019. FMD and mastitis disease detection in cows using Internet of Things (IOT). Procedia Computer Science 160:728-733.

Wang H, Qin J, Hou Q, *et al.,* 2020. Cattle face recognition method based on parameter transfer and deep learning. In Journal of Physics: Conference Series 1453(1):012054. IOP Publishing.

Wang J, Bell M, Liu X, *et al.,* 2020. Machine-learning techniques can enhance dairy cow estrus detection using location and acceleration data. Animals 10(7):1160.

Wang Y, Han D, Wang L, *et al.,* 2023. Contextualized Small Target Detection Network for Small Target Goat Face Detection. Animals 13(14):2365.

Wang Y, Mücher S, Wang W, *et al.,* 2023. A review of three-dimensional computer vision used in precision livestock farming for cattle growth management. Computers and Electronics in Agriculture 206:107687.

Wang Y, Zhang Y, Li J, *et al.,* 2021. Biogas energy generated from livestock manure in China: Current situation and future trends. Journal of Environmental Management 297:113324.

Wu Y, Liu M, Peng Z, *et al*., 2022. Recognising cattle behaviour with deep residual bidirectional LSTM model using a wearable movement monitoring collar. Agriculture 12(8):1237.

Xu B, Wang W, Falzon G, *et al.,* 2020. Automated cattle counting using Mask R-CNN in quadcopter vision system. Computers and Electronics in Agriculture 171:105300.

Xudong Z, Xi K, Ningning F, *et al.,* 2020. Automatic recognition of dairy cow mastitis from thermal images by a deep learning detector. Computers and Electronics in Agriculture 178:105754.

Yan B, Fan P, Lei X, *et al.,* 2021. A real-time apple targets detection method for picking robot based on improved YOLOv5. Remote Sensing 13(9):1619.

Yang L, Zhao J, Ying X, *et al.,* 2024. Utilization of deep learning models to predict calving time in dairy cattle from tail acceleration data. Computers and Electronics in Agriculture 225:109253.

Yıldız AK and Özgüven MM, 2022. Determination of estrus in cattle with artificial neural networks using mobility and environmental data. Journal of Agricultural Faculty of Gaziosmanpaşa University 39(1):40-45.

Yılmaz A, Uzun GN, Gürbüz MZ, *et al.,* 2021. Detection and Breed Classification of Cattle Using YOLO v4 Algorithm. International Conference on INnovations in Intelligent SysTems and Applications (INISTA), Kocaeli, Turkey, pp:1-4, doi: 10.1109/INISTA52262.2021.9548440.

Yin M, Ma R, Luo H, *et al.,* 2023. Non-contact sensing technology enables precision livestock farming in smart farms. Computers and Electronics in Agriculture 212:108171.

Yuan Q, Shen H, Li T, *et al.,* 2020. Deep learning in environmental remote sensing: Achievements and challenges. Remote Sensing of Environment 241:111716.

Zhang X, Li Y, Zhang Y, *et al.,* 2024. A new method to detect buffalo mastitis using udder ultrasonography based on deep learning network. Animals 14(5):707.

Zhao J, Zhang X, Yan J, *et al.,* 2021. A wheat spike detection method in UAV images based on improved YOLOv5. Remote Sensing 13(16):3095.

Zin TT, Phyo CN, Tin P, *et al*., 2018. Image technology-based cow identification system using deep learning. In Proceedings of the international multiconference of engineers and computer scientists. March 14-16, Hong Kong, Vol. 1, pp:236-247.

Zin TT, Misawa S, Pwint MZ, *et al*., 2020a. Cow identification system using ear tag recognition. In 2020 IEEE 2nd Global Conference on Life Sciences and Technologies (LifeTech) (pp:65-66). IEEE.

Zin TT, Seint PT, Tin P, *et al.,* 2020b. Body condition score estimation based on regression analysis using a 3D camera. Sensors 20(13):3705.

Zhu X, Lyu S, Wang X, *et al*., 2021. TPH-YOLOv5: Improved YOLOv5 based on transformer prediction head for object detection on drone-captured scenarios. In Proceedings of the IEEE/CVF international conference on computer vision Workshops, pp:2778-2788.