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Review

Application of Advanced Sensing and Intelligent Perception Technology in Smart Ranch: A Review with Emphasis on Chinese Grassland Pastoral Areas

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Abstract

Smart ranching stands at the forefront of digital transformation in modern animal husbandry, with sensing and intelligent perception technologies serving as the critical infrastructure of the perception layer. In contrast to existing reviews that have broadly surveyed generic technologies or global applications, this review systematically examines advanced sensing and intelligent perception technologies through three integrated perspectives—technical principles, system architecture, and application performance—with particular emphasis placed on forage-harvesting mechanization and intelligent livestock farming in the grassland pastoral areas of China. Although the underlying sensing principles are universally applicable, the adaptation challenges and bottleneck analyses presented herein are specifically contextualized to the environmental and operational conditions of northern Chinese grassland pastoral areas.

Keywords: smart ranch; sensing technology; intelligent perception; whole-process forage harvesting; precision livestock farming; multi-modal fusion

1. Introduction

1.1. Research Background and Scope

The global livestock sector accounts for over 30% of total agricultural output, with significant regional variations [1]. In China, beef and mutton production accounts for 12.9% of total meat output, and nearly 4 billion mu (approximately 2.67 million km^2) of natural grassland provides an abundant forage resource base for livestock development [2,3]. Nevertheless, traditional grazing systems have long been constrained by low production efficiency, resource-intensive practices, and lagging environmental governance. Empirical studies indicate that crude protein losses under traditional open-air sun-drying conditions can reach 30–50% [4]. Although the rate of information technology adoption in Chinese livestock farming reached 34.0% in 2021, the deployment of smart devices remained limited among small- and medium-sized farms [5]. By 2025, this disparity had further widened: automation levels in large-scale enterprises reached 92%, whereas small- and medium-sized operations achieved only approximately 18% [6]. Constrained by high costs and the

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absence of unified industry standards, sensing technologies have proven difficult to scale up, thereby impeding the modernization of herbivore livestock production [7].

In recent years, a steady stream of national policies has been issued to steer smart ranching and digital transformation across the livestock sector. The No. 1 Central Document of 2025 explicitly called for consolidating the foundation of livestock production and accelerating the modernization of grassland animal husbandry. The 2026 edition further advanced this agenda by emphasizing agricultural and rural modernization, promoting quality-oriented upgrading of scaled livestock operations, and fostering the deep integration of Internet of Things (IoT), artificial intelligence (AI), and other digital technologies with the grassland livestock industry [8]. These policy mandates establish sensing and intelligent perception as the indispensable foundational layer for digital transformation in grassland livestock production. Sensing and intelligent perception technologies, serving as the fundamental technical underpinning of smart ranching, constitute an effective approach to addressing the inefficiencies and suboptimal resource utilization inherent in traditional animal husbandry, and have consequently emerged as a focal research area in both academia and industry [9]. Given the distinctive climatic, economic, and infrastructural conditions of Chinese grassland pastoral areas—including extreme cold-dry winters, vast spatial scales, and heterogeneous farm sizes—this review specifically focuses on sensing and perception technologies applicable to these contexts, while acknowledging global technological advances that provide the underlying technical foundation. Accordingly, the scope of this review is twofold: to elucidate the international technical foundations of sensing and perception, and to contextualize these advances within the distinctive operational environment of Chinese grassland pastoral areas.

Smart ranching emerges from the convergence of precision agriculture and Internet of Things (IoT) technologies. Its operational paradigm rests upon sensor networks, data communication, and intelligent decision-making systems to enable end-to-end digital management spanning forage production, livestock breeding, and environmental regulation. From a value-chain perspective, smart ranching encompasses two principal domains: mechanized forage harvesting across the entire production cycle, including planting, mowing, tedding, baling, and storage-transportation operations; and intelligent livestock husbandry, involving precision feeding, health monitoring, behavior analysis, and environmental control. These two domains are intrinsically coupled, collectively constituting the technical architecture of modern smart ranching. Crucially, smart ranching departs from isolated precision agriculture or precision livestock farming in that it necessitates dynamic coupling between forage supply sensing and livestock demand perception.

Sensing and perception technologies constitute the foundation for field phenotypic information acquisition. Cheng et al. [10] noted that RGB cameras, laser scanning (LiDAR) sensors, thermal imaging sensors, multispectral and hyperspectral sensors, and fluorescence imaging sensors collectively represent the core modalities for phenotypic data acquisition, furnishing raw inputs for subsequent processing and analysis tasks such as crop growth monitoring, biomass estimation, and stress detection. Walter et al. [11] systematically reviewed advances in sensing technologies for precision livestock farming, emphasizing that multi-source information fusion is pivotal to achieving individual-level precision management. In recent years, the progressive maturation of multispectral and hyperspectral imaging, deep learning, and edge computing has significantly enhanced perception capabilities in smart ranching [12]. Most existing reviews, however, remain confined to individual technologies or isolated scenarios, lacking both cross-domain comparative assessment of sensing modalities and adequate attention to the adaptation challenges posed by complex field environments [13,14]. By integrating the two core operational domains of forage harvesting and livestock breeding, this paper systematically reviews

the application status, existing bottlenecks, and future directions of advanced sensing and intelligent perception technologies in smart ranching, while analyzing implementation barriers in the context of the industrial characteristics of Chinese grassland pastoral areas, thereby providing a reference for subsequent research and technology deployment.

1.2. Review Methodology

This review was conducted in accordance with a systematic literature-search protocol. The Web of Science, Scopus, IEEE Xplore, and CNKI databases were queried for peer-reviewed articles published between 2015 and 2026 using combinations of the following keywords: "smart ranching", "precision livestock farming", "forage harvesting", "sensing technology", "intelligent perception", "hyperspectral imaging", "livestock behaviour recognition", "edge computing", and "digital twin". Inclusion criteria were: (i) original research or review articles reporting on sensing or intelligent-perception technologies applied to forage production or livestock breeding; (ii) studies providing quantitative performance metrics (e.g., accuracy, R^2, MTBF); and (iii) publications in English or Chinese. Exclusion criteria were: (i) studies focused solely on crop (non-forage) production without livestock linkage; (ii) conference abstracts or grey literature lacking peer review; and (iii) articles reporting only conceptual frameworks without experimental validation. Following duplicate removal, a total of 312 records were retrieved; of these, 102 studies met the inclusion criteria and were analyzed for this review. Where multiple studies reported conflicting performance values for the same technology, priority was given to large-scale field trials over laboratory experiments, and to studies that disclosed dataset size, breed information, and evaluation metrics. Although the literature search was not geographically restricted, the synthesis and bottleneck analysis are intentionally oriented toward the conditions prevailing in northern Chinese grassland pastoral areas, where the transformation from traditional to smart ranching operations faces distinctive climatic and infrastructural constraints.

2. Smart Ranch Perception Technology System Framework

2.1. Ranch Sensor Classification and Characteristics

Based on monitoring objectives and application scenarios, and drawing on established frameworks for agricultural sensor taxonomy [15], sensors deployed in smart ranching environments can be classified into five categories: forage status sensors, soil and meteorological sensors, livestock status sensors, environmental sensors, and equipment operation sensors. These sensors operate synergistically to constitute the integrated ranch perception system, as illustrated in Figure 1.

2.1.1. Forage Status Sensors

Forage status sensors are primarily employed to acquire data on forage growth, nutritional composition, and physiological status, thereby informing harvest timing and forage quality control. Based on perception modality, these sensors can be categorized into two types: (1) direct-contact sensors, which obtain forage status parameters through physical contact; and (2) non-contact photoelectric sensors, which indirectly estimate forage quality indicators through spectral analysis and data modeling.

Portable chlorophyll fluorometers and stem strength sensors represent contact-based monitoring devices. The former assesses forage photosynthetic capacity by detecting maximum photochemical efficiency (Fv/Fm), thereby characterizing plant physiological stress [16]; the latter determines forage lignification levels via puncture resistance, thereby identifying optimal harvest windows. These devices offer low operational complexity and intuitive data presentation; however, they rely on manual point-by-point sampling and are unsuitable for rapid large-scale monitoring across extensive grasslands.

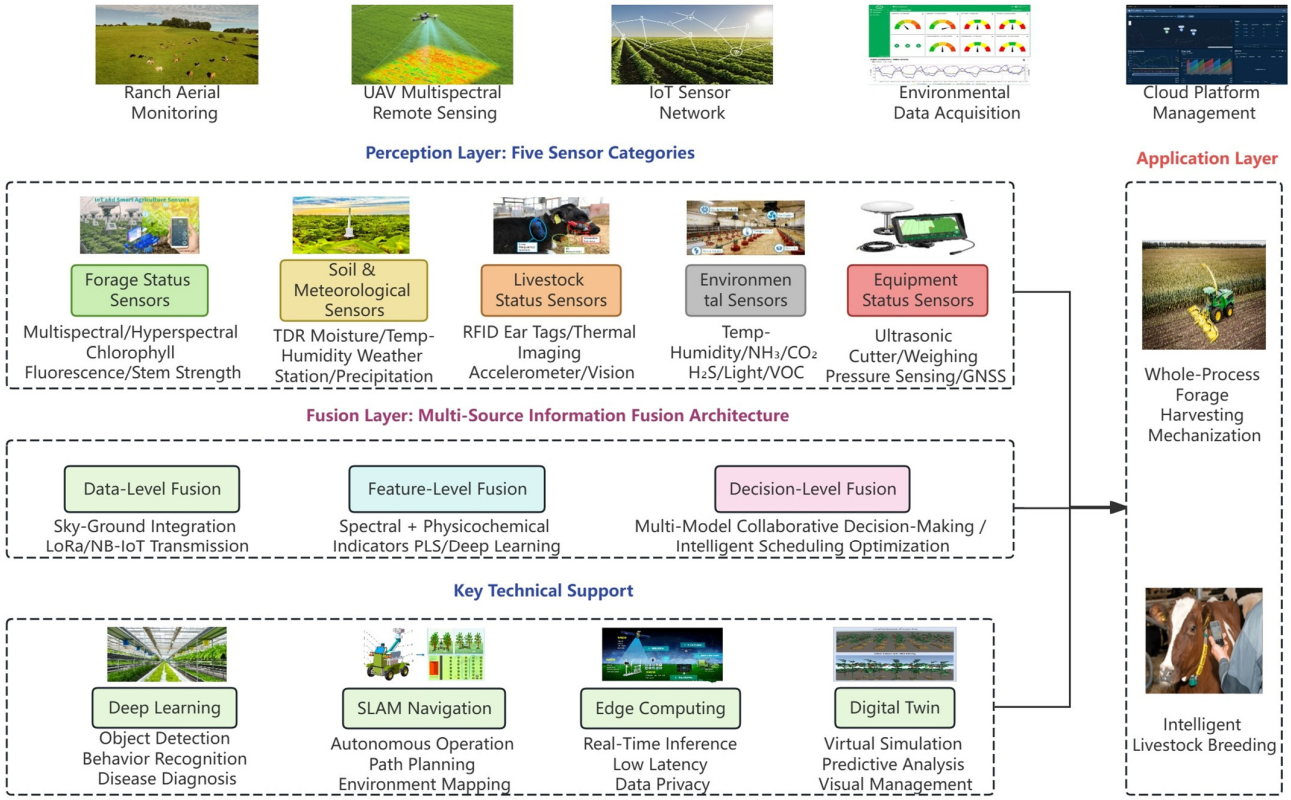

Figure 1. Classification system and application scenarios of smart ranching sensors. **Abbreviations:** UAV = Unmanned Aerial Vehicle; NDVI = Normalized Difference Vegetation Index; RVI = Ratio Vegetation Index; TDR = Time Domain Reflectometry; RFID = Radio-Frequency Identification; IMU = Inertial Measurement Unit; GNSS = Global Navigation Satellite System; NH_3 = Ammonia; CO_2 = Carbon Dioxide; H_2S = Hydrogen Sulfide; NDIR = Non-Dispersive Infrared; TMR = Total Mixed Ration; LoRa = Long Range; NB-IoT = Narrowband Internet of Things; PLS = Partial Least Squares.

Non-contact photoelectric sensors primarily comprise multispectral cameras and hyperspectral imagers. Multispectral cameras operate within the 400–1000 nm spectral range, capturing forage growth status through parameters such as the Normalized Difference Vegetation Index (NDVI) and the Ratio Vegetation Index (RVI) [17]. Qi et al. [18] utilized unmanned aerial vehicles (UAVs) equipped with hyperspectral imaging systems to acquire forage canopy spectral information, employing multi-granularity spectral segmentation to achieve effective estimation of crude protein content. Hyperspectral imagers achieve nanometer-level spectral resolution, enabling the detection of absorption features in the near-infrared band and the subsequent spectral inversion of component contents such as crude protein, neutral detergent fiber (NDF), and acid detergent fiber (ADF). Gao et al. [19] employed hyperspectral imaging combined with partial least squares (PLS) regression to establish a detection model for forage crude protein content. Following standard normal variate (SNV) preprocessing and feature band selection via the random frog algorithm, the model achieved a coefficient of determination (R^2) of 0.933. Nevertheless, the principal challenge confronting current forage status sensors resides in the trade-off between accuracy and cost: hyperspectral imaging offers high precision but at prohibitive expense (unit prices typically 5–10 times those of multispectral cameras), whereas multispectral imaging is cost-effective yet limited in detection scope. Optimal techno-economic configuration across different scales of ranching operations remains to be investigated.

2.1.2. Soil and Meteorological Sensors

Soil and meteorological sensors are employed to acquire environmental parameters governing forage growth, thereby furnishing data support for irrigation scheduling, harvest timing determination, and disaster warning. During forage production, comprehensive monitoring of soil moisture and meteorological conditions necessitates the acquisition of parameters including soil moisture content, temperature, air humidity, wind speed, and rainfall; commonly deployed sensors encompass soil moisture sensors, temperature sensors, and automatic weather stations.

Soil moisture monitoring data constitute the core basis for irrigation scheduling. Time Domain Reflectometry (TDR) sensors enable layered monitoring of soil moisture content, achieving measurement accuracies of ±2–±3% [20,21]. Yu et al. [20] reviewed advances in soil moisture sensing, noting that Frequency Domain Reflectometry (FDR) and TDR represent the current mainstream technologies, each exhibiting distinct application scenarios and technical characteristics. PT100 platinum resistance temperature sensors achieve an accuracy of ±0.1 °C for soil temperature monitoring [22]. The northern Chinese grassland pastoral areas pose particular challenges for soil sensor deployment: winter frozen soil layers can reach 1.5–2.0 m in thickness, and traditional TDR equipment exhibits substantially diminished measurement stability under freeze–thaw conditions. This necessitates the urgent development of dedicated soil moisture sensors and complementary monitoring solutions capable of withstanding temperatures as low as −40 °C.

Automatic weather stations integrate temperature, humidity, wind speed, rainfall, and solar radiation sensors, thereby furnishing meteorological inputs for forage growth models. Distributed meteorological monitoring networks enable precise characterization of microclimatic variability across ranching operations, thereby informing harvest window prediction. Ion-selective electrodes (ISEs) are further employed for soil nutrient ion monitoring (e.g., N, P, K, pH), enabling selective detection of specific ion species at parts-per-million (ppm) resolution while serving as a low-cost alternative to laboratory chemical analysis for assessing soil fertility at the ranching scale.

2.1.3. Livestock Status Sensors

Livestock status monitoring encompasses three dimensions: physiological status, behavioral activity, and positional trajectory, directly underpinning individual health management, precision feeding strategies, and reproductive management. To comprehensively acquire livestock status information, technologies including infrared thermal imaging, wearable sensing devices, and computer vision are commonly employed, with sensor modalities typically comprising infrared thermal imaging sensors, ear-tag temperature sensors, triaxial accelerometers, and intelligent cameras.

(1) Body temperature monitoring sensors: Infrared thermal imaging sensors achieve temperature resolutions of approximately 0.05–0.1 °C, enabling non-contact rapid screening of group-level body temperature [23]. Xiao et al. [23] proposed an automatic pig ear temperature extraction algorithm based on infrared thermal imaging, thereby furnishing a technical reference for livestock thermometry. Ear-tag temperature sensors enable continuous individual-level body temperature monitoring, achieving sampling intervals of 5–15 min and capturing daily temperature patterns and abnormal fluctuations.

(2) Behavioral monitoring sensors: Triaxial accelerometer-based wearable devices identify activities such as feeding, rumination, and lying through motion pattern analysis, with recognition accuracies typically reaching 85–95% under experimental conditions [24]. Li et al. [25] achieved individual behavior monitoring and recognition for caged chickens using accelerometer sensors, thereby furnishing experimental evidence for wearable sensing applications in animal husbandry.

(3) Visual monitoring devices: Computer vision systems enable non-contact monitoring of group behavior through deep learning algorithms. He et al. [26] systematically reviewed advances in intelligent animal information perception and behavior detection within precision livestock farming. A persistent challenge confronting current livestock wearable sensors lies in balancing endurance and adaptability: when sampling frequency exceeds 1 Hz, behavioral recognition accuracy improves, yet device endurance is reduced from weeks to days; conversely, reducing sampling frequency risks the loss of critical behavioral data.

2.1.4. Environmental Sensors

In northern Chinese grassland pastoral areas, these environmental sensors encounter additional reliability challenges under extreme climatic conditions, which are elaborated in Section 6.1. Environmental sensors constitute the data source for intelligent regulation of livestock housing environments. Temperature and humidity sensors are deployed in stratified arrangements at varying heights within the housing, achieving typical temperature accuracies of ± 0.1–± 0.5 °C and humidity accuracies of ± 2–± 5% RH [27]. Electrochemical ammonia sensors typically feature a measurement range of 0–100 ppm and are widely applied in environmental monitoring of livestock housing [27]. Non-Dispersive Infrared (NDIR) carbon dioxide sensors are employed for ventilation feedback control. Additional sensors include hydrogen sulfide sensors and light sensors [27]. Lian et al. [27] developed an intelligent inspection robot equipped with environmental indicator monitoring modules, enabling real-time acquisition of indoor temperature, humidity, lighting, and harmful gas parameters, thereby furnishing novel approaches for multi-dimensional environmental data monitoring in caged poultry housing. Song et al. [28] employed high-sensitivity electrochemical sensors for online monitoring of ammonia emissions from growing-finishing pig housing, revealing daily average exhaust ammonia concentrations of approximately 9.85 mg/m^3, with local concentrations peaking at 38.36 mg/m^3 during high-temperature periods, thereby furnishing empirical data to inform ammonia sensor range design.

2.1.5. Equipment Operation Sensors

Equipment status sensors are employed to acquire operational parameters of forage harvesting machinery and feeding equipment, thereby furnishing data support for operation quality control and equipment maintenance management. To monitor equipment operational status in real time, parameters including cutting platform height, operation weight, compression pressure, and vibration frequency are typically collected, with sensor modalities commonly encompassing ultrasonic and laser radar ranging sensors, weighing sensors, pressure sensors, and piezoelectric accelerometers.

Ultrasonic and laser radar-based cutting platform height sensors typically feature detection ranges of 0.2–2 m and accuracies of approximately ± 1 cm, thereby constituting core components for automatic cutting platform height regulation [29]. Weighing sensors are employed in Total Mixed Ration (TMR) ingredient formulation and yield measurement, achieving typical accuracies of ± 0.5–± 1%. Pressure sensors are employed for bale density control, thereby ensuring uniform and compliant bale density. Piezoelectric accelerometers are employed for mechanical fault diagnosis, enabling the identification of abnormal states such as bearing wear and blade damage through vibration spectrum analysis. Jin et al. [30] reviewed advances in online yield monitoring for grain combine harvesters, noting that weighing-based and impact-based methods represent the two mainstream yield monitoring approaches. Nevertheless, the reliability of forage harvesting equipment sensors in harsh environments characterized by dust and vibration remains a critical issue constraining large-scale application; the Mean Time Between Failures (MTBF) of existing commercial

sensors in ranching environments is typically below 500 h, substantially below the 5000 h achievable in indoor industrial scenarios.

The various sensor categories and their technical application pathways for smart ranching are summarized in Figure 2.

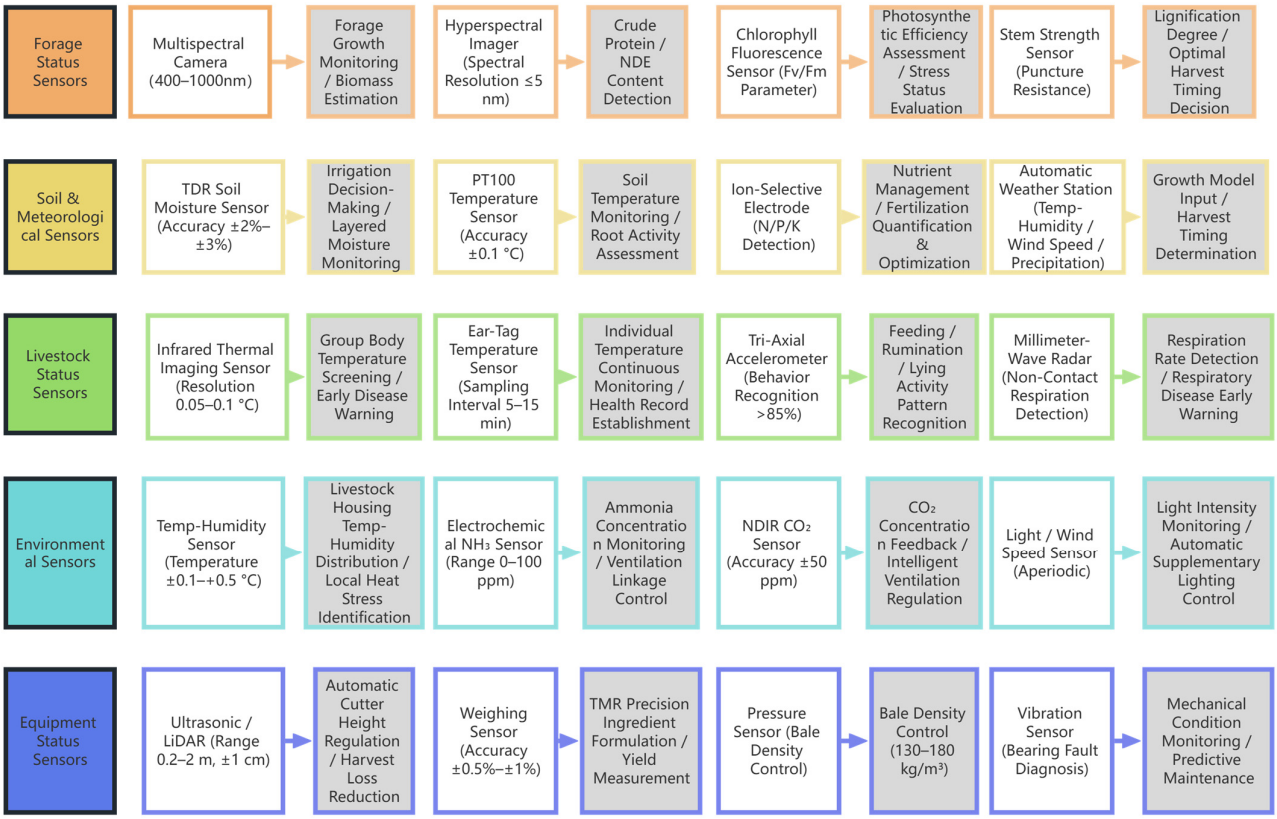

Figure 2. Technical pathways for multi-sensor applications in smart grassland ranching. **Abbreviations:** NDVI = Normalized Difference Vegetation Index; RVI = Ratio Vegetation Index; NDF = Neutral Detergent Fiber; ADF = Acid Detergent Fiber; Fv/Fm = Maximum Photochemical Efficiency of Photosystem II; TDR = Time Domain Reflectometry; FDR = Frequency Domain Reflectometry; PT100 = Platinum Resistance Thermometer; ISE = Ion-Selective Electrode; RFID = Radio-Frequency Identification; NDIR = Non-Dispersive Infrared; TMR = Total Mixed Ration; GNSS = Global Navigation Satellite System; IMU = Inertial Measurement Unit; UWB = Ultra-Wideband.

2.2. Ranch Multi-Source Information Fusion Architecture

Although the sensor categories described above furnish multi-dimensional data for ranching operations, any single sensor is inherently constrained by environmental noise, measurement error, and spatial limitations. Multi-source information fusion is therefore essential to enhance detection accuracy and system robustness. Different sensors can acquire multi-dimensional daU+2013ta for ranching operations; however, single sensors remain susceptible to interference from environmental noise, measurement errors, and spatial limitations, resulting in insufficient monitoring accuracy and reliability [15]. Multi-source information fusion technology, through the integration of multi-sensor data, effectively enhances detection accuracy and system robustness, and has emerged as a key technical architecture for the perception layer in smart ranching. Zhai et al. [15] reviewed advances in intelligent measurement and control technology for agricultural machinery, noting that multi-sensor information fusion represents a key technical pathway for enhancing agricultural equipment intelligence. For example, the combination of ultrasonic and infrared sensors with Kalman filtering algorithms enables precise tillage depth detection; similarly, multi-source fusion approaches employing inclinometers, ultrasonic sensors, and MEMS

inertial sensors facilitate operational status perception [15]. Multi-source information fusion in smart ranching perception systems can be classified into three hierarchical levels based on processing depth: data-level fusion, feature-level fusion, and decision-level fusion.

Data-level fusion represents the most fundamental and lowest-level fusion approach, entailing direct comprehensive processing of raw multi-sensor data. Through the deployment of soil sensor networks, meteorological stations, UAV remote sensing, and ground-based equipment, integrated air–ground data acquisition systems have been established [21]. IoT-based systems leveraging cloud computing, wireless sensor networks, and big data analytics have been developed for intelligent agricultural operations, encompassing automated wireless-controlled irrigation and forage growth monitoring in smart ranching environments. Nevertheless, practical deployment is hindered by substantial disparities in sampling frequencies across sensors—soil sensors typically operating at 10–30 min intervals, visual sensors at 30 fps, and inertial measurement units (IMUs) above 100 Hz—thereby posing significant challenges for data synchronization.

Feature-level fusion entails extracting features following data acquisition, thereby striking a balance between data compression and information preservation. In the context of forage quality detection, for instance, the fusion of multispectral vegetation indices (at centimeter-level spatial resolution), hyperspectral absorption features (at nanometer-level spectral resolution), and laboratory reference data enables the construction of quality prediction models using Partial Least Squares (PLS) or deep learning algorithms. Gao et al. [19] demonstrated that inversion models for forage crude protein content based on hyperspectral images achieved favorable predictive performance under cross-validation. Du et al. [31] employed Near-Infrared Spectroscopy (NIRS) in conjunction with chemometric methods for quantitative analysis of natural forage nutritional components, achieving cross-validation coefficients of determination (R^2) exceeding 0.98 for crude protein. Table 1 presents a detailed comparison of four primary forage quality detection technologies.

Table 1. Performance comparison of primary forage quality detection technologies.

Technology Type	Detection Indicators	Accuracy (R^2)	Spatial Resolution	Primary Limitations	Ref.
Multispectral imaging	NDVI, biomass	0.75–0.85	Centimeter-level	Limited indicators, highly susceptible to illumination	[17,32]
Hyperspectral imaging	Crude protein, NDF, ADF	0.90–0.95	Centimeter-level	Large data volume, complex processing, high cost	[18,19]
Near-infrared spectroscopy	Crude protein, moisture	0.95–0.98	Point measurement	Requires calibration models, destructive sampling	[30]
Chlorophyll fluorescence	Fv/Fm, photosynthetic efficiency	Primarily qualitative	Point measurement	Reflects only physiological status, not quality indicators	[16]

Note: In terms of cost level, multispectral imaging is low (<50,000 Chinese Yuan, CNY), near-infrared spectroscopy is medium (50,000–150,000 CNY), and hyperspectral imaging is high (>150,000 CNY). NDVI = Normalized Difference Vegetation Index; RVI = Ratio Vegetation Index; NDF = Neutral Detergent Fiber; ADF = Acid Detergent Fiber; Fv/Fm = Maximum Photochemical Efficiency of Photosystem II; SNV = Standard Normal Variate; PLS = Partial Least Squares; NIRS = Near-Infrared Spectroscopy.

As evident from Table 1, hyperspectral imaging and near-infrared spectroscopy achieve outstanding detection accuracy, yet each presents inherent limitations: the former entails prohibitive costs and complex data processing, whereas the latter necessitates destructive sampling and demonstrates limited model transferability; multispectral imag-

ing is cost-effective and suited to large-area monitoring, yet is limited in detection scope; chlorophyll fluorescence enables rapid assessment of physiological stress status, yet cannot directly invert nutritional quality indicators. Accordingly, optimal sensor configurations should be tailored to the scale of ranching operations and specific detection objectives.

Following feature extraction and information fusion, operational decisions in smart ranching are predicated upon fused data. Ranch management systems integrate forage growth models, livestock nutritional requirement models, and meteorological forecasts to generate harvest schedules and feeding strategies, thereby realizing a perception-driven, data-informed management paradigm. Figure 3 illustrates the complete hierarchical architecture of the smart ranching technical system and the primary data content at each level.

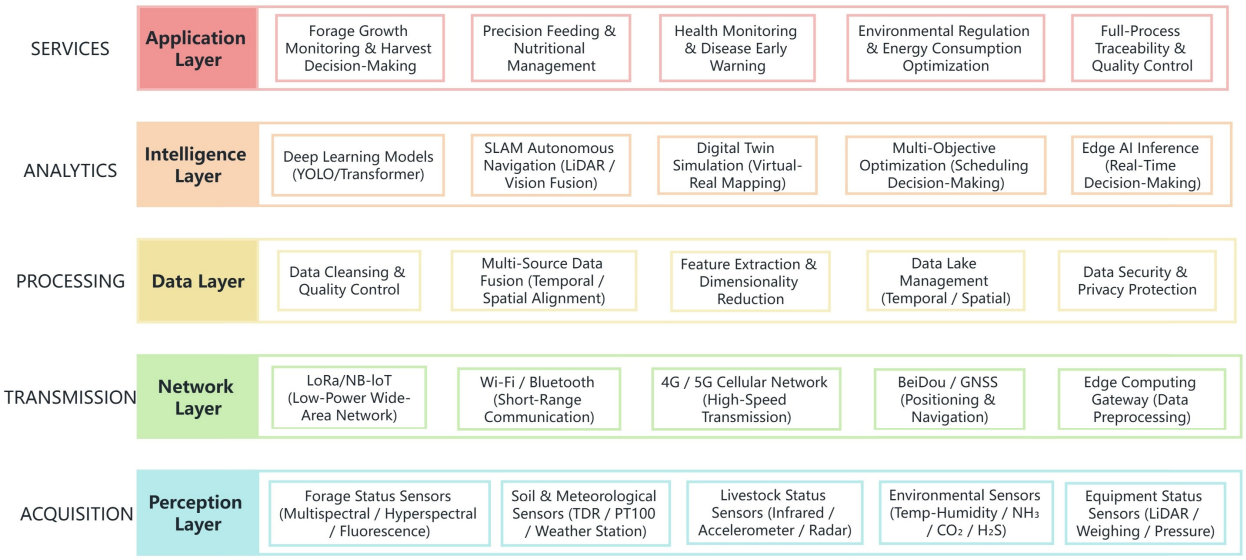

Figure 3. Hierarchical architecture of the smart ranching technical system. **Abbreviations:** YOLO = You Only Look Once; SLAM = Simultaneous Localization and Mapping; LiDAR = Light Detection and Ranging; UAV = Unmanned Aerial Vehicle; GNSS = Global Navigation Satellite System; LoRa = Long Range; NB-IoT = Narrowband Internet of Things; 4G/5G = Fourth/Fifth Generation Cellular Network; BeiDou = BeiDou Navigation Satellite System; Edge AI = Edge Artificial Intelligence.

The above sensor classification framework establishes the perception foundation for ranching operations based on the target entities monitored (i.e., forage, soil, livestock, environment, and equipment). The subsequent sections are organized around the two principal production domains: whole-process forage harvesting and intelligent livestock farming. The sensor types deployed in each domain correspond to the aforementioned classification. Through three integrated dimensions—technical principles, system composition, and application effectiveness—the subsequent analysis specifically examines the integrated application and bottleneck challenges of advanced sensing and intelligent perception technologies in smart ranching.

3. Sensing Technologies in Whole-Process Forage Harvesting Mechanization

The intelligent technology system for whole-process forage harvesting mechanization illustrated in Figure 4 integrates multispectral imaging, LiDAR, near-infrared spectroscopy, GNSS positioning, and other multi-source sensors with intelligent algorithms across five major operational stages: growth monitoring, intelligent harvesting, tedding and drying, baling control, and multi-machine coordination. This enables end-to-end digitalization and intelligent management spanning forage growth assessment, low-loss harvesting, precise drying control, bale quality assurance, and scaled operation scheduling, thereby furnishing

comprehensive technical support for forage quality enhancement, efficiency gains, and loss minimization.

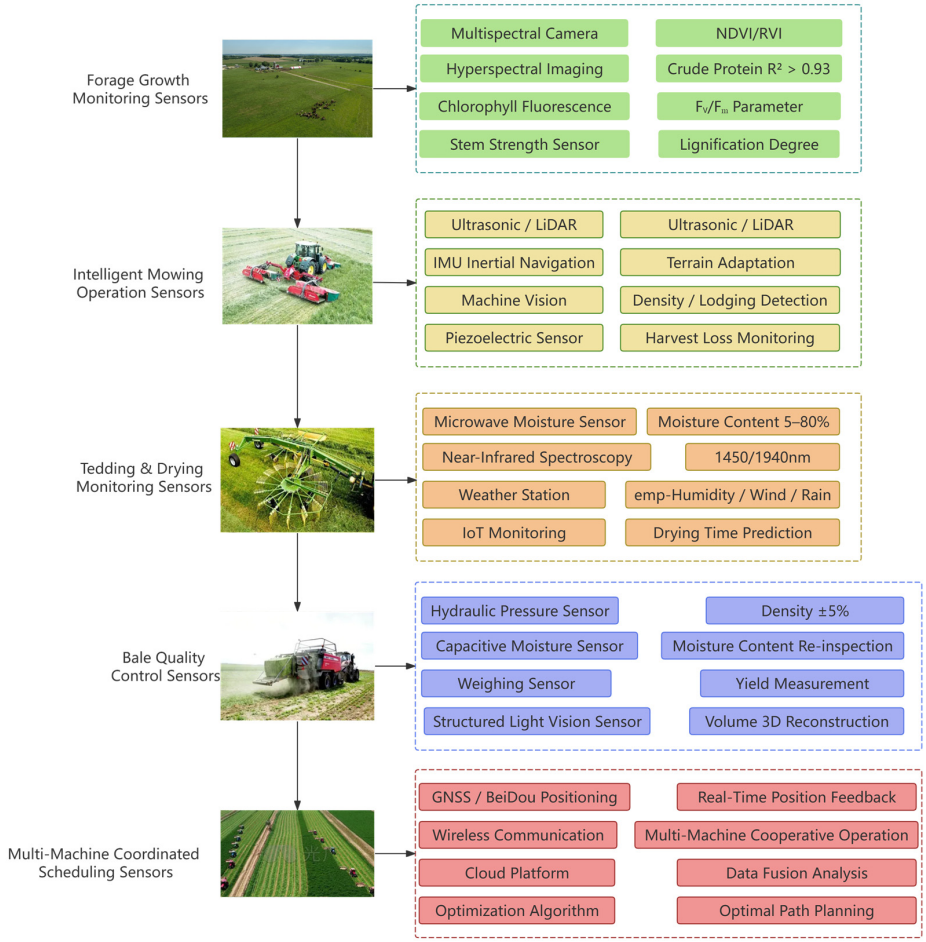

Figure 4. Intelligent technology system for whole-process forage harvesting mechanization. **Abbreviations:** NDVI = Normalized Difference Vegetation Index; RVI = Ratio Vegetation Index; Fv/Fm = Maximum Photochemical Efficiency of Photosystem II; LiDAR = Light Detection and Ranging; IMU = Inertial Measurement Unit; GNSS = Global Navigation Satellite System; NIR = Near-Infrared.

The five operational stages—growth monitoring, intelligent mowing, tedding and drying, baling control, and multi-machine coordination—are addressed in Sections 3.1–3.5, respectively.

3.1. Forage Growth Status Perception Technology

Precise perception of forage growth status constitutes the prerequisite for determining harvest timing and ensuring harvest quality. Monitoring objectives for forage growth status can be categorized into three dimensions: biomass and coverage, forage species identification and nutritional quality, and physiological stress status and maturity assessment.

(1) Biomass and coverage monitoring: UAVs equipped with multispectral cameras acquire forage canopy parameters such as the Normalized Difference Vegetation Index (NDVI) and the Ratio Vegetation Index (RVI), which are combined with ground quadrat data to establish biomass estimation models [17]. Chen et al. [32] validated the effectiveness of multispectral remote sensing for crop growth monitoring during cotton production management; with appropriate parameter optimization, this approach is equally applicable to forage biomass estimation. Reinermann et al. [33] reviewed remote sensing technologies for grassland production and management, noting that biomass estimation models based on multispectral parameters can achieve R^2 values above 0.80 under homogeneous grass-

land conditions. However, accuracy degrades significantly in mixed vegetation areas (R^2 declining to 0.50–0.60), indicating that spatial heterogeneity is a key factor affecting remote sensing estimation accuracy.

(2) Forage species identification and nutritional quality: Hyperspectral imaging can distinguish leguminous from gramineous forage through analysis of differences in spectral reflectance features within the 900–1700 nm band, thereby informing harvest strategy adjustment. This technology also enables rapid estimation of nutritional indicators such as crude protein, NDF, and ADF [31]. Gao et al. [19] employed hyperspectral imaging in conjunction with PLS regression to establish a detection model for forage crude protein content. Following SNV preprocessing and feature band selection via the random frog algorithm, the model achieved a coefficient of determination (R^2) of 0.933. Qi et al. [18] proposed a multi-granularity spectral segmentation method in their research on forage crude protein estimation based on UAV hyperspectral remote sensing, effectively improving inversion accuracy for low-content physicochemical indicators. Du et al. [31] employed NIRS combined with chemometric methods for quantitative analysis of natural forage nutritional components, achieving cross-validation coefficients of determination (R^2) exceeding 0.98 for crude protein. Nevertheless, the aforementioned research is predominantly based on laboratory or small-scale field experiments; the transferability of models across different varieties, growth stages, and regional forages has not been adequately verified, constituting the primary obstacle to commercial application of hyperspectral technology.

(3) Physiological stress and maturity judgment: At the ground-based perception level, soil moisture sensor networks are typically deployed at 50–100 m intervals to monitor soil moisture content at different depths. Yu et al. [20] reviewed advances in soil moisture sensing, noting that TDR sensors generally achieve measurement accuracies of ±2–±3% and are suitable for layered monitoring at 10 cm, 20 cm, and 40 cm depths. Stem strength sensors assess the degree of lignification via puncture resistance measurement; when alfalfa stem puncture resistance exceeds a critical threshold, NDF content begins to rise rapidly, thereby serving as a reference for determining the critical harvest period.

Chlorophyll fluorescence technology can be employed for rapid, non-destructive detection of plant nutritional status and maturity assessment. Through OJIP (OJIP fluorescence transient) testing to acquire fluorescence induction curve parameters, such as φPo (maximum quantum yield of photosystem II (PSII)), φEo (electron transport quantum yield), and PI^{Total} (performance index), nutrient element deficiencies in plants can be identified [16]. Under normal growth conditions, φPo values are approximately 0.79; when nutritional stress occurs, φPo, φEo, and PI^{Total} significantly decrease, while Fo and ABS/RC (absorption flux per reaction center) increase, reflecting damage to photosynthetic apparatus function. The Fv/Fm value reflects the maximum photochemical efficiency of photosystem II in plants, normally around 0.8 under normal conditions, and significantly decreases when subjected to drought, low temperature, and other stresses. Comprehensive analysis combining fluorescence parameters and spectral features enables more thorough judgment of forage physiological status and harvest suitability. However, chlorophyll fluorescence technology is currently primarily employed in research scenarios, and its equipment portability and field operational convenience are insufficient to support large-scale production applications.

The performance differences among these forage-quality detection technologies are not merely numerical; they reflect fundamental trade-offs in sensing physics, data-processing complexity, and operational constraints. Multispectral imaging achieves moderate accuracy (R^2 = 0.75–0.85) because its broad spectral bands (typically 10–20 nm in width) obscure subtle absorption features of crude protein and fiber; its low cost, however, renders it suitable for large-area monitoring in ranching operations where spatial coverage outweighs precision.

Hyperspectral imaging attains $R^2 > 0.90$ by resolving nanometer-level absorption bands, yet this precision comes at the cost of massive data volume (hundreds of spectral channels per pixel), complex preprocessing requirements (SNV, derivative correction), and extreme sensitivity to illumination geometry and atmospheric scattering—factors that account for the 10–35 percentage-point decline in accuracy from laboratory to field conditions. Near-infrared spectroscopy (NIRS) offers the highest laboratory accuracy (R^2 = 0.95–0.98) because its point-measurement geometry eliminates spatial mixing of plant tissues, but its destructive sampling requirement and poor model transferability across forage varieties and growth stages limit field applicability. Chlorophyll fluorescence, while rapid and non-destructive, captures only photosynthetic efficiency (Fv/Fm and φPo) rather than biochemical composition; its inability to directly invert protein or fiber content renders it complementary to, rather than a substitute for, spectral methods. Accordingly, the selection among these technologies should be governed not by a single accuracy metric, but by the specific operational objective—whether large-area screening, precision harvest timing, or laboratory validation—and by the environmental conditions under which the sensor must operate.

3.2. Intelligent Perception System for Mowing Equipment

Intelligent mowing systems primarily rely on three integrated subsystems: terrain perception, crop perception, and quality feedback. The automatic cutting-platform height-regulation system employs ultrasonic sensor arrays or LiDAR to detect ground undulations in real time, in conjunction with Inertial Measurement Unit (IMU) attitude sensors, and regulates cutting-platform hydraulic cylinders via proportional–integral–derivative (PID) control algorithms. Existing commercial intelligent cutting-platform systems achieve centimeter-level height-control accuracy in hilly grasslands, thereby reducing harvesting losses relative to traditional fixed-height approaches. Ultrasonic sensors typically feature detection ranges of 0.2–2 m and accuracies of approximately ± 1 cm, together with rapid response characteristics that render them suitable for real-time control scenarios [33]. However, substantial dust generated during forage harvesting causes signal attenuation in ultrasonic sensors; although LiDAR demonstrates superior dust resistance, its cost is approximately 3–5 times that of ultrasonic sensors.

Machine-vision-based systems for forage density and lodging detection identify density distributions and lodging areas through deep learning algorithms, dynamically adjusting cutter rotational speed and forward speed to achieve adaptive harvesting [34]. Loss sensors (piezoelectric or photoelectric) detect fallen-grass losses in real time, triggering alarms when loss rates exceed predetermined thresholds.

Cutting-platform height-control precision constitutes a key factor affecting forage harvesting losses. Traditional mowers rely on operator experience for manual cutting-platform height adjustment, often resulting in missed cuts or excessively high stubble in hilly grasslands with pronounced ground undulations. Intelligent cutting-platform systems achieve automatic height control through multi-sensor fusion schemes (ultrasonic sensors, IMUs, and GNSS (Global Navigation Satellite System)), thereby reducing harvesting losses by 10–20% under experimental conditions, as reported in industry tests [29]. The aforementioned performance data predominantly derive from ideal test conditions; in actual ranching environments, factors including dust, vibration, and electromagnetic interference can degrade sensor accuracy by 20–40%, constituting an engineering challenge that remains to be addressed for the large-scale deployment of intelligent cutting platforms.

3.3. Tedding and Drying Process Monitoring Technology

Tedding and drying constitute a critical stage connecting mowing and baling in the forage harvesting process. The core objective is to reduce forage moisture content from

an initial 60–75% to 15–25%, a range suitable for baling via sun-drying [35]. Moisture content represents the most critical monitoring indicator at this stage, directly affecting final harvest quality and storage effectiveness. Forage with moisture content exceeding 25% is prone to mold and deterioration after baling, whereas moisture content below 10% leads to increased leaf shedding and harvesting losses. Therefore, real-time monitoring of moisture content and dynamic adjustment of tedding frequency and harvest progress based thereon are critical for ensuring forage quality.

Currently, notable progress has been achieved in online monitoring technologies for the tedding and drying stage. Hartfiel et al. [35] conducted alfalfa harvesting experiments focusing on tedding processes, investigating the effects of this operation on forage drying rate and nutritional components. Their research demonstrated that timely tedding after mowing can approximately double the drying rate, whereas continued tedding when moisture content drops below 30% exhibits significantly diminished efficacy in accelerating drying, thereby furnishing a theoretical basis for determining optimal tedding timing. Lim et al. [36] explored the use of portable spectroradiometers and handheld Normalized Difference Vegetation Index (NDVI) meters for estimating field-drying forage moisture content, finding a significant correlation between NDVI values and forage moisture content, with a corresponding coefficient of determination (R^2) of 0.79 and a root mean square error (RMSE) of 8.58%. UAV-mounted multispectral imaging equipment improves estimation accuracy to R^2 = 0.89 and RMSE = 6.74%, thereby furnishing a technical foundation for large-area field drying monitoring. Regarding sensor hardware, Benning et al. [37] developed an online forage moisture monitoring system based on multi-frequency dielectric detection. Based on the principle that the dielectric constant of forage varies with moisture content, this device employs a multi-frequency synchronous detection method to eliminate interference arising from differences in forage density and component composition, and can be directly mounted on harvesting machinery for real-time moisture measurement. Yu et al. [38] proposed an IoT-based crop drying digital management system, integrating temperature and humidity sensors, load sensors, and cameras to achieve real-time monitoring of the drying process, and developed a deep learning-based dryness prediction model achieving a coefficient of determination (R^2) of 0.985, enabling precise determination of drying endpoints and thereby verifying the feasibility of IoT technology application in field drying environments.

At present, intelligent monitoring technologies for the tedding and drying stage still face numerous challenges. Although microwave moisture sensors and near-infrared spectroscopy-based online detection can determine forage moisture content, they are primarily suited to final detection prior to baling, whereas real-time moisture monitoring specifically targeting the tedding process remains insufficient. Microwave moisture sensors exploit the absorption of microwaves by water molecules, with measurement ranges typically covering 5–80%, accuracies of approximately ±1–±2%, and response times below 1 s. Near-infrared spectroscopy-based online detection calculates moisture content through analysis of water absorption feature bands near 1450 nm and 1940 nm, offering the advantage of non-destructive detection. The integration of IoT monitoring networks, meteorological data, and forage drying models can enable advance prediction of overall drying duration [38]. However, the stability of this method under intense solar radiation in pastoral areas has not been adequately verified, and the effects of uneven forage spreading and fluctuating swath thickness on detection accuracy during tedding still require further investigation, constituting challenges that must be addressed to facilitate the transition from experimental validation to field deployment. Once forage moisture has been sufficiently reduced through tedding and drying, the material proceeds to baling—the final operation in the forage harvesting process.

3.4. Bale Quality Control Sensing Technology

Baling represents the final operation in the forage harvesting process, and bale quality control constitutes the critical stage, ensuring bale density, moisture content, and weight through real-time monitoring to furnish a quality foundation for subsequent storage, transportation, and feeding. Bale quality control encompasses four stages: density control, moisture content re-inspection, weight measurement, and quality grading.

(1) Density control: Hydraulic pressure sensors continuously collect pressure data during baling operations, working in conjunction with closed-loop control algorithms to maintain consistent bale density. This intelligent pressure-feedback regulation system significantly improves bale density uniformity and enhances storage and transportation stability. By comparison, high-density bales during open-air storage exhibit dry matter losses reduced by over 50% relative to low-density bales. According to industry standards (GB/T 25423–2023) [39], leguminous forage baling density should be $\geq$150 kg/m^3, gramineous forage $\geq$130 kg/m^3, and rice or wheat straw $\geq$100 kg/m^3.

(2) Moisture content re-inspection: Microwave or capacitive moisture sensors can perform re-inspection of bale moisture content prior to baling, automatically pausing operations and triggering alarms when thresholds are exceeded, thereby preventing non-compliant bales from entering storage and transportation.

(3) Weight measurement and quality grading: Weighing sensors provide real-time statistics on individual bale mass; combined with GNSS positioning data, these enable the mapping of spatial yield distribution across ranching operations. The structured-light vision measurement method proposed by Yin et al. [40] furnishes a novel technical means for quality control during baling. This technology relies on three-dimensional reconstruction to obtain bale volume, which is combined with weight data to calculate density, ultimately enabling online bale quality grading. The objective of bale quality control is to reduce energy consumption and improve operational efficiency while ensuring bale density. Real-time pressure-sensor feedback enables compression mechanisms to automatically adjust compression force based on forage characteristics, thereby avoiding unnecessary energy consumption from over-compression.

Currently, sensing technologies applied to bale quality control are relatively mature, yet the achievement of multi-parameter collaborative optimization still presents challenges. Subsequent research may focus on two directions: multi-objective collaborative regulation of density, moisture content, and weight; and compression characteristic modeling for different forage varieties and moisture contents.

3.5. Whole-Process Coordinated Scheduling System for Forage Harvesting

The multi-machine coordinated scheduling system for forage harvesting relies on multi-sensor fusion technology to achieve operational progress monitoring and formation coordination, with the overall architecture detailed in Figure 5. Each harvesting machine is equipped with BeiDou/GNSS positioning devices and wireless communication modules, enabling real-time upload of positional data, travel speed, operational area, and other operational parameters. The scheduling system integrates constraints encompassing forage moisture content, weather forecasts, and equipment operational status, and employs intelligent optimization algorithms to generate harvest sequences and travel paths. At present, agricultural machinery coordination systems primarily employ LiDAR, visual sensors, and BeiDou positioning devices for environmental perception, subsequently enhancing positioning accuracy and operational stability through multi-source data fusion, and enabling low-latency data interaction via 5G and agricultural IoT networks. At the decision-making level, the system dynamically assigns operational tasks and plans travel paths based on field conditions, meteorological information, and equipment status [41].

Qian et al. [42] reviewed advances in intelligent control technologies for unmanned farms, noting that multi-machine coordinated scheduling constitutes one of the core technologies for enhancing large-scale farm operational efficiency.

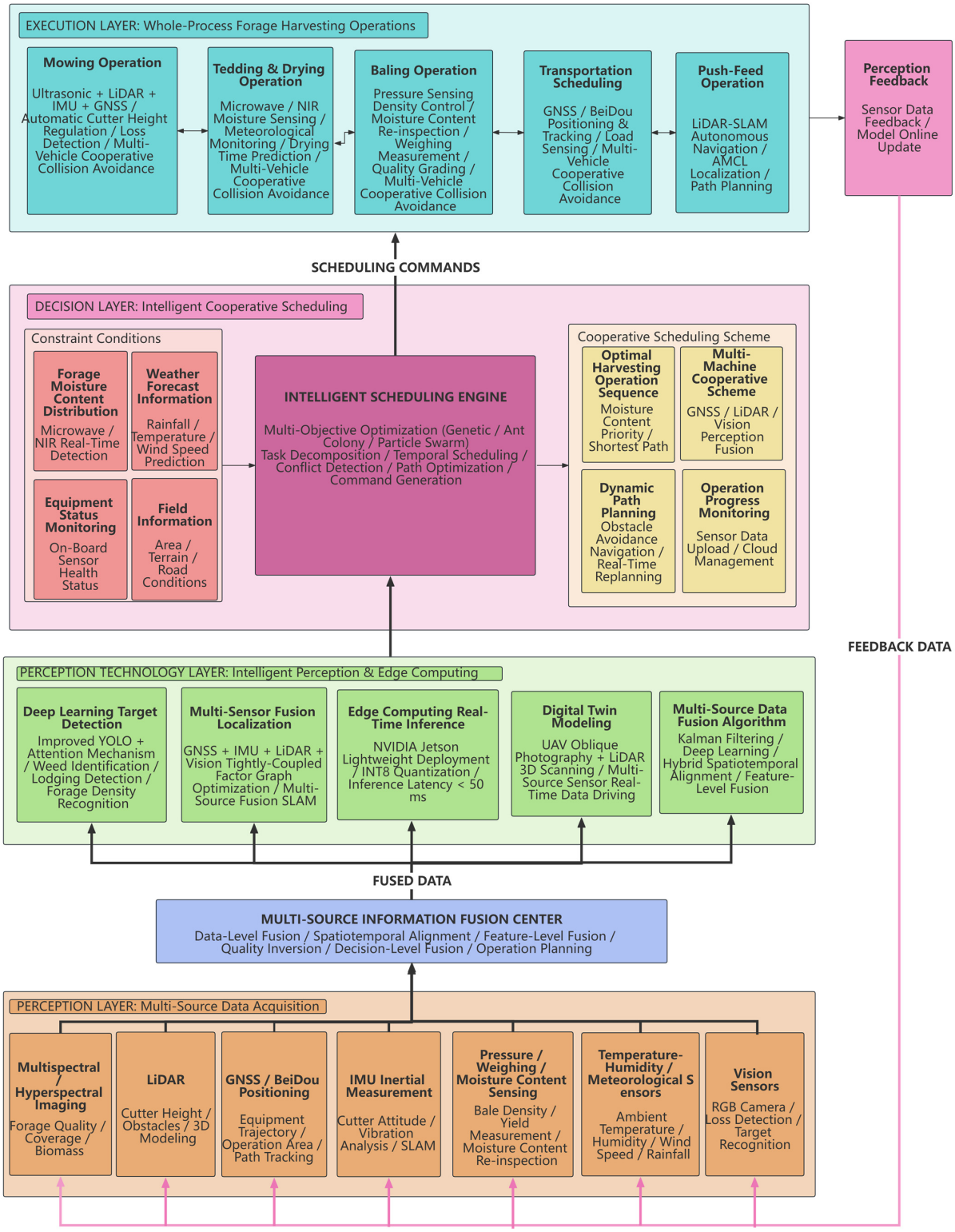

Figure 5. Whole-process coordinated scheduling for forage harvesting. **Abbreviations:** GNSS = Global Navigation Satellite System; BeiDou = BeiDou Navigation Satellite System; IMU = Inertial Measurement Unit; LiDAR = Light Detection and Ranging; SLAM = Simultaneous Localization and Mapping; AMCL = Adaptive Monte Carlo Localization; YOLO = You Only Look Once; INT8 = 8-bit Integer Quantization; UAV = Unmanned Aerial Vehicle.

The adoption of intelligent scheduling schemes in lieu of manual planning reduces machinery travel distance by more than 15%; with relaxed operational time constraints, reductions can exceed 20% [43], thereby significantly reducing fuel consumption and improving operational efficiency. Onboard sensors transmit operational data to cloud-based management platforms, where such data are integrated with meteorological information and forage maturity indices to automatically generate optimal harvest paths and operational sequences, thereby minimizing machinery idling and redundant operations. Current coordinated scheduling systems are predominantly designed for large-scale flat farmland, thereby limiting their applicability to the fragmented plots, complex road conditions, and weak network signals typical of northern Chinese grassland pastoral areas. Consequently, the development of lightweight scheduling solutions tailored to small- and medium-scale ranching operations is urgently required.

4. Sensing Technologies in Intelligent Livestock Farming

In intelligent breeding systems, sensing technology serves as the core enabler of precision livestock management and data-driven process optimization, while constituting the critical foundation linking information perception, intelligent decision-making, and precise control across the entire breeding chain [44]. To systematically delineate the integrated application of sensing technologies in livestock breeding, this section describes a technical system encompassing individual identification, precision feeding, health monitoring, environmental regulation, and behavior analysis. The corresponding sensing technology architecture for intelligent livestock breeding is illustrated in Figure 6.

4.1. Individual Identification, Precision Feeding Perception, and Control Systems

Individual identification and precision feeding constitute the foundational processes of intelligent breeding, relying on various sensing devices to achieve livestock identity verification and precise feed delivery tailored to individual requirements. These processes encompass three core technologies: individual identification, body weight and size estimation, and precise feed intake control.

(1) Individual identification technology: RFID (radio-frequency identification) electronic ear tags represent a mature approach to livestock individual identification, achieving reading distances of 0.5–2 m and accuracies exceeding 99% under standard operating conditions. Xu et al. [45] reviewed monitoring technologies for precision poultry breeding, noting that RFID exhibits signal interference and reading conflicts in large-scale intensive breeding scenarios. Computer vision-based non-contact identification has advanced rapidly, employing deep learning algorithms to extract facial and body texture features for identity determination. Zhang et al. [46] developed a lightweight cattle face recognition model based on DenseNet121, which achieved 93.54% recognition accuracy in complex breeding environments. This model significantly reduced computational complexity while maintaining recognition accuracy through the introduction of depthwise separable convolutions and channel attention mechanisms. Lv [47] investigated non-contact individual identification for beef cattle via deep learning algorithms, employing the TLAINS-InceptionV3 model for body side identification of Simmental and Angus cattle and achieving 99.74% accuracy. Non-contact identification can reduce management costs associated with ear tag damage and loss. Mora et al. [48] integrated computer vision algorithms with RFID systems to achieve identification and tracking of group-housed pigs, thereby furnishing experimental validation for the complementary application of the two technologies.

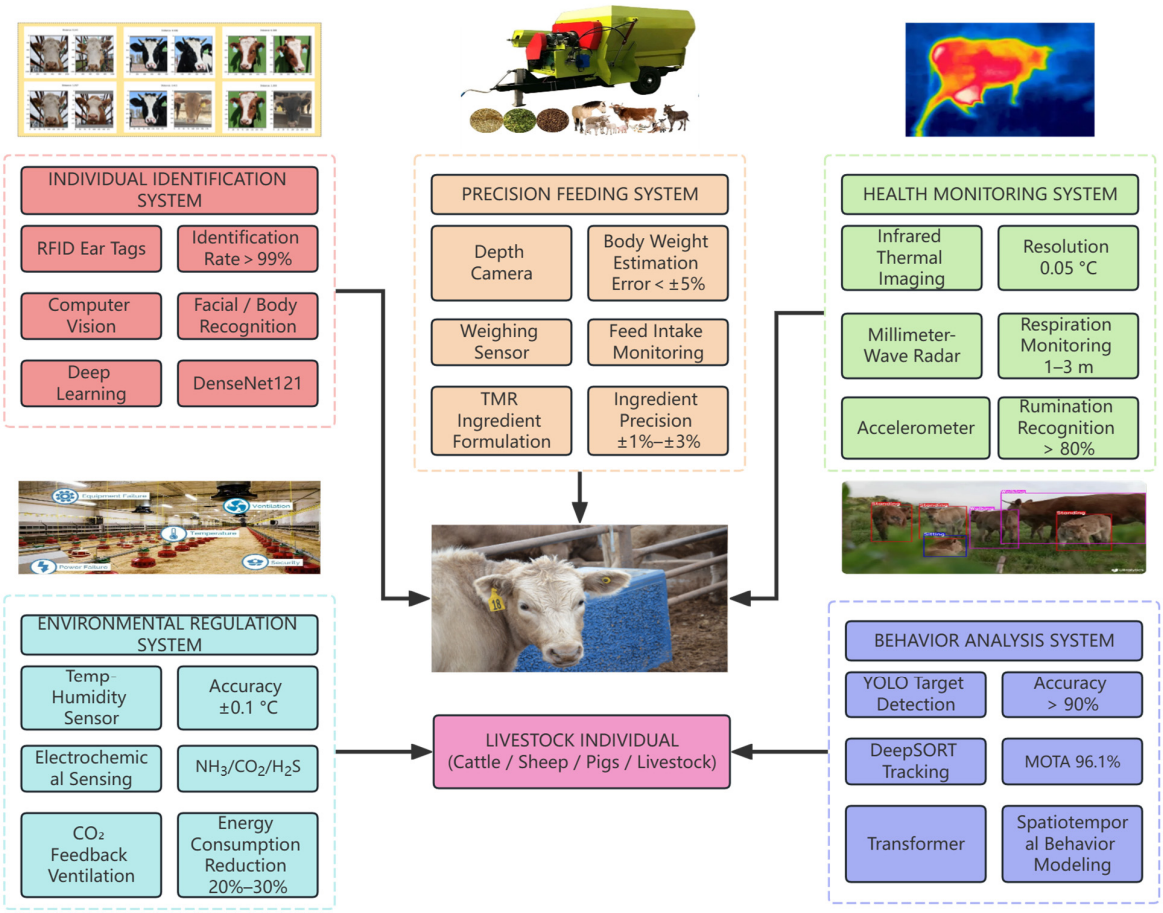

Figure 6. Sensing technology architecture for intelligent livestock farming. **Abbreviations:** RFID = Radio-Frequency Identification; TMR = Total Mixed Ration; UWB = Ultra-Wideband; YOLO = You Only Look Once; DeepSORT = Deep Simple Online and Realtime Tracking; MOTA = Multiple Object Tracking Accuracy; IDF1 = Identification F1 Score; NH_3 = Ammonia; CO_2 = Carbon Dioxide; H_2S = Hydrogen Sulfide.

(2) Body weight and size estimation: Depth camera-based non-contact body weight estimation extracts morphological parameters—including body length, chest circumference, and withers height—via three-dimensional reconstruction, which is subsequently integrated with machine learning regression models for body weight prediction, achieving estimation errors typically within ±5% [49]. This technology mitigates the stress induced by traditional weighing methods, rendering it suitable for routine growth monitoring. In recent years, this approach has advanced considerably in algorithmic optimization and expanded application. Kongsro [50] employed Microsoft Kinect depth cameras to acquire dorsal depth images of pigs, establishing body weight prediction models through back contour feature extraction. This approach achieved average errors within 4–5%, thereby verifying the feasibility of consumer-grade depth cameras for livestock body weight estimation. Condotta et al. [51] employed Kinect v2 depth sensors for mass estimation of growing-finishing pigs, enabling individual mass prediction based on depth information in group-housed environments. Results indicated that prediction accuracy under standing postures was significantly superior to that under lying postures, thereby underscoring the importance of posture standardization for improving estimation accuracy. Ruchay et al. [52] developed a non-rigid three-dimensional reconstruction method for live cattle using three Kinect v2 depth cameras. Through multi-view point cloud registration and non-rigid shape recovery, complete three-dimensional models were constructed, enabling high-precision automated measurement of body size parameters. This furnishes novel technical means

for cattle body type assessment and genetic selection. Dohmen et al. [53] conducted a systematic review of computer vision-based livestock body weight estimation, analyzing 87 publications from 2000 to 2021. Their analysis indicates that RGB-D (red–green–blue–depth) cameras and multi-view stereo imaging represent the current mainstream 3D data acquisition methods, whereas deep learning methods outperform traditional regression models in feature extraction and body weight prediction. Pezzuolo et al. [54] employed Kinect v1 depth cameras to acquire pig surface point cloud data. Body size parameters were obtained via structured light three-dimensional reconstruction, and body weight prediction models were established using linear regression and neural networks. Field experiments demonstrated that this method achieved a mean absolute percentage error below 3.5%.

Collectively, these studies demonstrate that depth camera technology has achieved considerable maturity for livestock body weight estimation. Nevertheless, model generalizability across different species, growth stages, and complex breeding environments remains a critical bottleneck limiting large-scale deployment. Future research should prioritize the development of universal models for diverse livestock species and the enhancement of depth imaging under extreme illumination conditions, and deployment of simpler, lightweight models on edge computing devices.

(3) Precision feeding control: Control systems integrate the above sensing outputs with actuators—such as automated feed dispensers and environmental regulators—to close the perception-decision-execution loop. The core of precision feeding lies in dynamically adjusting feeding formulas and delivery quantities based on individual livestock characteristics (breed, age, body weight, production stage) and real-time status (health condition, environmental temperature), with precision feeding technology capable of improving feed conversion rates by 5–12% while reducing nitrogen and phosphorus emissions. Feed intake monitoring can be achieved through weighing sensors and level sensors in feed troughs to monitor feed delivery and remaining quantities [55]. Total Mixed Ration (TMR) precision feeding mixer trucks equipped with weighing sensors and ingredient control systems can achieve ingredient precision of ±1–±3% [56]. After RFID identification of individual identity, the system automatically calls the individual's historical data and management plans, achieving differentiated precision allocation [48]. Long et al. [57] developed a mobile monitoring platform for livestock housing integrating UWB (Ultra-Wideband) wireless positioning and multi-category sensing devices, capable of achieving comprehensive environment and position information collection inside and outside breeding areas, providing data support for cluster-based feeding management in large-scale ranches.

At present, precision feeding systems are predominantly designed for intensive breeding scenarios such as dairy cattle and pigs, and exhibit limited adaptability to the mixed grazing-and-supplementary-feeding model for beef cattle and sheep in northern Chinese grassland pastoral areas. The development of low-cost, integrated identification-and-feeding solutions tailored to extensive grazing conditions constitutes an urgent challenge that remains to be addressed.

4.2. Livestock Health Monitoring Sensing Technology

Health monitoring constitutes a core application domain of smart ranching perception, with the objective of enabling early disease detection and warning through multi-sensor fusion. It encompasses four dimensions: body temperature monitoring, respiration monitoring, rumination behavior monitoring, and comprehensive score-based warning.

(1) Body temperature monitoring: Infrared thermal imaging devices are typically installed above feeding passages, automatically acquiring temperature distribution data of livestock heads and bodies. The pig ear temperature automatic extraction algorithm developed by Xiao et al. [23] also provides a novel implementation path for automated

body temperature screening. Infected animals typically exhibit temperature deviations from normal baselines that are distinguishable by thermal imaging, thereby enabling the detection of abnormalities prior to the onset of clinical symptoms [23]. However, infrared thermal imaging is substantially constrained by environmental temperature, animal hair length, and measurement distance, and its screening reliability in outdoor grazing scenarios has yet to be rigorously validated.

(2) Respiration monitoring: Respiration rate represents an important physiological indicator reflecting livestock heat stress status and respiratory system health. Millimeter-wave radar provides a non-contact modality for livestock respiration monitoring. Utilizing Frequency-Modulated Continuous Wave (FMCW) and Doppler principles, minute chest and abdominal displacements are non-invasively captured; subsequently, respiration signals are resolved through phase-change analysis, thereby enabling respiration-rate detection within a 1–3 m range for the early screening of respiratory diseases. In recent years, significant advances have been achieved in livestock respiration monitoring using radar technology. Tuan et al. [58] pioneered the application of a 77 GHz FMCW radar system for dairy cow respiration monitoring, developing an intelligent node integrating radar with temperature and humidity sensors. Deployed in milking parlors, this system continuously measures flank displacement data and implements machine learning-based algorithms for presence-state determination, timestamp marking, and individual respiration-rate matching. Compared with manual observation, the system achieved an R^2 of 0.995 and an RMSE of 1.582 breaths/min, operating continuously for one year without failure. These results demonstrate the feasibility of FMCW radar as a low-cost automated solution for dairy cow respiration measurement. In parallel, Pastell et al. [59] developed a non-contact dairy cow respiration-rate measurement system based on laser distance sensors, acquiring respiration waveforms through radial displacement monitoring of the flank surface. This system exhibited high consistency with manual observations and was suitable for fixed-facility scenarios, including milking robots, milking parlors, and tie-stall housing.

Collectively, these studies demonstrate that non-contact sensing technologies—including millimeter-wave radar and laser ranging—hold considerable promise for livestock respiration monitoring. Compared with traditional manual counting, these methods offer distinct advantages, such as continuous monitoring, stress-free operation, and high automation, thereby providing real-time data support for heat-stress warning and early screening of respiratory diseases. Nevertheless, current technologies remain constrained by several challenges, including multi-target identification and tracking, motion-artifact suppression, and signal stability under extreme environmental conditions (e.g., high temperature, high humidity, and strong wind), necessitating further optimization of algorithm robustness and system integration. Notably, existing validations of millimeter-wave radar for respiration monitoring have been conducted almost exclusively within confined barns. Large-scale open-grazing environments introduce additional challenges, including multi-target aliasing, long-distance livestock movement, and complex background clutter, which have yet to be adequately addressed through field experiments.

(3) Rumination behavior monitoring: Collar-mounted sensors incorporating tri-axial accelerometers can detect chewing movements and neck posture, enabling the identification of feeding and rumination behaviors through machine learning algorithms. Abnormal rumination serves as an important indicator of diseases such as subacute ruminal acidosis, with early-recognition accuracy exceeding 80% under experimental conditions. Li et al. [25] implemented individual behavior monitoring and recognition for caged chickens using accelerometer sensors, achieving a 92.7% average recognition accuracy for behaviors including feeding, drinking, standing, and lying. Tedeschi et al. [60] provided a comprehensive review of recent advances in sensor technology and intelligent decision-making tools for

precision livestock farming, emphasizing that the fusion of wearable sensors and artificial intelligence represents an inevitable trend toward individual-level health management.

(4) Comprehensive scoring-based warning: Health management platforms integrate multiple physiological indicators—including body temperature, respiration, rumination, and feed intake—to construct comprehensive evaluation models. When individual data deviates from the species-specific normal baseline, the system automatically triggers warnings, prompting management personnel to investigate abnormalities promptly. Lian et al. [27] developed an intelligent inspection robot equipped with environmental monitoring, body-temperature detection, sound monitoring, and behavior surveillance modules, enabling automatic alarm triggering and disease warning under abnormal conditions. Tu et al. [61] proposed a behavior recognition and tracking method for group-housed pigs based on an improved DeepSORT algorithm, effectively addressing individual-tracking challenges under occlusion and providing technical support for group-level health monitoring. The health-management decision-making process is illustrated in Figure 7.

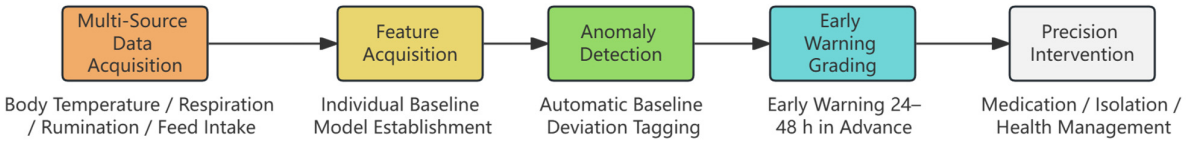

Figure 7. Health management decision-making process.

4.3. Livestock Behavior Recognition and Analysis Technology

Livestock behavior recognition and analysis aims to automatically identify and track behavioral patterns through sensing technologies, thereby supporting health monitoring, welfare assessment, and reproductive management. This field is primarily categorized into two methodological paradigms: wearable-sensor-based behavior recognition and computer-vision-based non-contact behavior analysis.

(1) Wearable-sensor-based behavior recognition: Tri-axial accelerometers, gyroscopes, and other inertial sensors are typically deployed on livestock necks or legs to collect motion data, from which behaviors such as feeding, rumination, lying, and walking are identified through machine learning algorithms. This approach offers high data precision and enables the acquisition of individual-level continuous behavior records, constituting an important technical means for fine-grained individual management in precision livestock farming. In recent years, significant advances have been witnessed in sensor optimization, deep-learning algorithm application, and multi-modal data fusion for this technology. Mao et al. [62] presented a comprehensive review of animal activity recognition based on wearable sensors and deep learning, systematically summarizing the applications of fully connected neural networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants in behavioral classification. They highlighted that CNNs exhibit outstanding performance in extracting time-series features, whereas long short-term memory (LSTM) networks and their gated recurrent unit (GRU) variants possess unique advantages in capturing temporal dependencies of animal behaviors. Furthermore, they outlined critical challenges—including scarce labeled data, class imbalance, and cross-domain generalization—and proposed corresponding potential solutions. Shebiah et al. [63] proposed a dairy cow behavior recognition system combining neck-mounted and leg-mounted accelerometers. Utilizing MPU6050 six-axis sensors to collect accelerometer and gyroscope data, they employed Decision Tree, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest (RF) algorithms to classify six behaviors: walking, standing rest, feeding, lying rest, lying rumination, and standing rumination. The Random Forest algorithm achieved the highest accuracy of 89.5%, thereby verifying the effectiveness of multi-position sensor fusion and ensemble learning in fine-grained

behavior recognition. Essien et al. [64] developed a novel wearable nose-ring sensor with a built-in tri-axial accelerometer to collect dairy cow nasal movement data during feeding, rumination, and walking. They subsequently compared and evaluated the classification performance of Random Forest, Artificial Neural Network, Gated Recurrent Unit, and CNN-LSTM hybrid models. Results showed the GRU model performed best with 97.78% accuracy, and revealed the decisive role of *X*-axis (rostro-caudal, i.e., forward–backward) motion features in behavior classification through SHAP (SHapley Additive exPlanations) and LIME(Local Interpretable Model-agnostic Explanations) explainable AI techniques.

Yue et al. [65] proposed a class-specific feature selection strategy for wearable cattle behavior recognition. By designing differentiated feature selection schemes tailored to the unique motion patterns of distinct behavioral categories, they effectively mitigated confusion between similar behaviors—such as feeding versus rumination, and lying versus standing rest—achieving a 4.2 percentage point improvement in classification accuracy over traditional unified feature selection methods on public datasets.

Ni et al. [66] constructed a comprehensive end-to-end analytical framework for livestock behavior modeling and health assessment, integrating wearable electronic recording systems with machine learning methodologies. This framework enables integrated processing from raw sensor data acquisition and preprocessing through feature extraction to behavior classification and health scoring, while supporting real-time data stream processing and online model updating. Consequently, it provides a systematic solution for large-scale automated behavior monitoring in ranch environments.

Benaissa et al. [67] fused Ultra-Wideband (UWB) positioning data with accelerometer measurements, utilizing positional information to assist in distinguishing spatially separated behaviors, such as feeding and drinking. This approach effectively overcomes the limitations of single-sensor systems in recognizing behaviors with similar motion patterns, improving the overall behavior classification F1-score by 6.3%.

Collectively, wearable sensor-based approaches have yielded considerable research advances in livestock behavior recognition; however, numerous practical challenges persist during field implementation. Practical constraints—including inconvenient device attachment, limited battery endurance, and poor adaptability to livestock physiology—significantly hinder the long-term, large-scale deployment of such devices [62]. Specifically, high-frequency sampling (exceeding 1 Hz) enhances behavioral recognition accuracy yet reduces device endurance from weeks to days, whereas low-frequency sampling risks the omission of critical behavioral features. Furthermore, inter-species and inter-individual behavioral variations, together with data distribution shifts induced by changes in sensor placement, pose substantial challenges to model generalization. Future research should prioritize low-power hardware design, passive and semi-passive sensing technologies, and the application of transfer learning and federated learning for cross-domain model adaptation. Additionally, multi-modal sensor fusion—integrating inertial, acoustic, and positioning data—should be explored to enhance the discriminative capacity for similar behaviors.

(2) Computer vision-based non-contact behavior analysis. The utilization of deep learning algorithms for high-throughput, non-contact livestock monitoring represents a prominent contemporary research direction. Representative studies include the application of YOLO (You Only Look Once) series models to livestock target detection, which have achieved detection accuracies exceeding 90% for major species such as dairy cattle and pigs under controlled experimental conditions [68]. Table 2 presents a performance comparison of major deep learning models for livestock behavior recognition.

Tu et al. [61] proposed a behavior recognition and tracking method for group-housed pigs based on an improved DeepSORT algorithm. This method effectively addresses individual tracking challenges under occlusion conditions, achieving a Multiple Object

Tracking Accuracy (MOTA) of 96.1% and an Identification F1 Score (IDF1) of 98.0%, as demonstrated by experimental validation.

Table 2. Performance comparison of major deep learning models for livestock behavior recognition.

Model/Method	Target Animal	Recognized Behavior	Detection Accuracy	Frame Rate/ Speed	Main Innovation
Improved-YOLOv8 + Bot-SORT	Beef Cattle	Multi-Target Detection/Behavior Tracking	mAP 94.8%	Real-Time	FBCD-YOLOv8n/ Integrated Behavior Recognition and Tracking
Improved Deep SORT	Group-Housed Pigs	Behavior Recognition/ Individual Tracking	MOTA 96.1% IDF1 98.0%	30 fps	Occlusion Handling/Group Behavior Analysis
Improved BCE-YOLO	Dairy Cattle	Feeding Behavior Detection	Precision 77.73%	Real-Time	Video+ Improved BCE-YOLO Front/Top View
YOLOv5n + Channel Pruning	Dairy Cattle	Estrus Behavior Recognition	Accuracy 97.70%	Real-Time	Lightweight Model2,239-Frame Dataset
Shuffle Net-Triplet	Dairy Cattle	Individual Body Weight Recognition	Accuracy 92.3%	Real-Time	Lightweight Network Natural Scenarios
Improved-OpenPose121	Beef Cattle	Facial Recognition/Individual Identification	Accuracy 93.54%	Real-Time	Lightweight Design Complex Environment Adaptation
3D CNN-BiLSTM	Dairy Cattle	Gait Recognition/ Individual Identification	Accuracy 95.5%	Non-Real-Time	3D Convolution + Temporal Features

Note: mAP = mean Average Precision; BoT-SORT = Boosted Object Tracking with Simple Online and Realtime Tracking; FBCD = Feature-Based Classification Detector; MOTA = Multiple Object Tracking Accuracy; IDF1 = Identification F1 Score; fps = frames per second.

Qin et al. [69] reviewed applications of machine vision technology in animal husbandry, highlighting that deep learning has achieved substantial advances in behavior recognition, body condition scoring, and anomaly detection. He et al. [26] systematically reviewed early-stage research progress in intelligent animal information perception and behavior detection within precision livestock farming, identifying computer vision as a critical pathway for non-contact livestock monitoring.

Behavior recognition networks based on the Transformer architecture, which model spatiotemporal relationships, exhibit superior discriminative capacity for similar behaviors compared with traditional convolutional neural networks. Bai et al. [70] utilized an improved YOLOv5s network for multi-scale dairy cow behavior recognition. Wang et al. [71] combined YOLO5n lightweight target detection models with channel pruning for dairy cow estrus behavior recognition, attaining a detection accuracy of 97.70% on a dataset comprising 2239 frames of estrus behavior. Li et al. [72] employed deep detectors for posture and drinking behavior recognition in group-housed pigs, achieving an average precision of 98.9%; however, they noted that factors such as pen occlusion in real-world environments compromise detection stability. Rohan et al. [68] summarized applications of deep learning in livestock and poultry behavior recognition, observing that existing studies predominantly focus on pigs and dairy cows, whereas research on other livestock species—such

as beef cattle, mutton sheep, and poultry—with markedly different behavioral patterns remains insufficient.

From an implementation perspective, monitoring systems establish individual baseline models by statistically analyzing the temporal allocation of behaviors for each animal, automatically triggering warnings when behavioral patterns deviate from established baselines. Group-level behavior analysis evaluates collective stress levels and welfare status through the calculation of activity uniformity indicators. Nevertheless, key challenges in behavior recognition technology arise from the complexity of real breeding environments, which encompass illumination variations, occlusion, dust, and animal-to-animal interference, all of which substantially reduce the actual detection accuracy of deployed models. Indeed, behavioral recognition accuracy under laboratory conditions typically exceeds that observed in actual ranch environments by 15–25 percentage points [68], and model generalization capability represents a critical bottleneck that urgently requires resolution in current research.

In summary, although deep learning has achieved high accuracy under controlled conditions, the absence of standardized benchmarks and the complexity of real ranch environments remain critical barriers to practical deployment.

4.4. Intelligent Perception and Regulation of the Livestock Housing Environment

Livestock housing environmental perception systems monitor temperature, humidity, air quality, lighting, and ventilation parameters through multi-dimensional sensor networks. Specifically, distributed temperature and humidity sensors, deployed at multiple heights at predefined intervals, enable the identification of localized overheating or excessive humidity zones [27]. Table 3 Summarizes ammonia sensors, which typically operate on electrochemical principles with measurement ranges of 0–100 ppm, are critical for assessing air quality in livestock housing [28]. Song et al. [28] reported that the daily average exhaust ammonia concentration in growing-finishing pig housing reached approximately 9.85 mg/m^3, with localized peaks of 38.36 mg/m^3 during high-temperature periods. Consequently, real-time ammonia monitoring is essential for safeguarding livestock health. Integrated multi-function electrochemical sensors incorporating ammonia, temperature, and humidity modules, along with built-in 4G communication and data transmission capabilities, have been developed to address these requirements, achieving measurement accuracies of ±2% full scale and response times below 10 s.

Table 3. Monitoring standards and sensor configurations for key parameters in the livestock housing environment.

Environmental Parameter	Optimal Range (Growing-Finishing Pigs)	Sensor Type	Measurement Principle	Typical Accuracy	Sensor Deployment Requirements	Regulation Strategy
Temperature	18–26 °C (Varies with Body Weight)	PT100 Platinum Resistance/ DS18B20 Digital	Resistance Temperature Effect/Digital Temperature Sensing	±0.1–0.5 °C	0.5–2 m Above Ground, Avoid Direct Heat Sources	Fan/Evaporative Cooling Pad/ Heater Linkage Control
Relative Humidity	50–70%	Capacitive/ resistive	Humidity-Sensitive Element Dielectric Constant Variation	±2–5% RH	Deployed Adjacent to Temperature Sensors	Mist Humidification/Ventilation Dehumidification

Table 3. *Cont.*

Environmental Parameter	Optimal Range (Growing-Finishing Pigs)	Sensor Type	Measurement Principle	Typical Accuracy	Sensor Deployment Requirements	Regulation Strategy
Ammonia (NH_3)	<20 ppm (Recommended < 10 ppm)	Electrochemical/ Metal Oxide	Redox Reaction/ Semiconductor Gas Sensing	±5% FS(0–100 ppm)	Above Manure Gutter/Near Ventilation Openings/ 0.5–1.5 m Above Ground	Increase Ventilation Rate/Spray Denitrification
Carbon Dioxide (CO_2)	<3000 ppm (Recommended < 1500 ppm)	NDIR (Non-Dispersive Infrared)	Infrared Absorption Spectrum (4.26 μm)	±50 ppm	Housing Center/Respiratory Zone Height	Variable Frequency Ventilation/CO_2 Feedback Control
Hydrogen Sulfide (H_2S)	<10 ppm (Recommended < 5 ppm)	Electrochemical	Electrochemical Oxidation Reaction Current	±1 ppm	Downwind of Manure Treatment Area	Enhanced Local Ventilation in Manure Discharge Area
Light Intensity	50–100 lux (Finishing Period)	Photoresistor/ Photodiode	Photoelectric Effect/ Photovoltaic Effect	±5%	Uniformly Distributed in Housing Center	Timed Supplementary Lighting/Photoperiod Management
Wind Speed	0.1–0.3 m/s (Winter)	Hot-Wire/Vane Anemometer	Thermal Conduction/ Mechanical Rotation	±0.1 m/s	Air Inlet/ Housing Center/ Air Outlet	Variable Frequency Fan Staged Speed Regulation

Note: PT100 = Platinum Resistance Thermometer; DS18B20 = Digital Temperature Sensor; NH_3 = Ammonia; CO_2 = Carbon Dioxide; H_2S = Hydrogen Sulfide.Furthermore, intelligent ventilation systems with carbon dioxide concentration linkage control adjust fan operational status based on real-time monitoring data, thereby reducing energy consumption by 20–30% compared with conventional timed ventilation modes. Wen et al. [73], in their review of intelligent robot applications in layer hen breeding, emphasized that sensor feedback-based environmental regulation constitutes a critical component of precision breeding. Light sensors continuously monitor natural light intensity, automatically adjusting supplementary lighting activation and brightness according to photoperiod management requirements. Moreover, integrated systems combine environmental parameters, weather forecasts, and livestock status to establish predictive warning models, enabling proactive adjustment of regulation strategies prior to the arrival of extreme weather events.

However, most existing environmental regulation systems are designed for enclosed livestock housing, whereas northern pastoral regions in China predominantly utilize semi-open and fully open shed structures, where seasonal temperature differentials can reach 65 °C. Consequently, the measurement ranges and precision configurations of conventional sensors are inadequately adapted to these specialized operational scenarios.

5. Key Intelligent Perception Technologies for Smart Ranching

Sections 3 and 4 have elaborated on the application status of various sensors within specific scenarios across the two principal production chains of forage harvesting and livestock breeding. This section shifts focus to the common intelligent perception technologies underpinning these multi-scenario applications—namely, deep learning-driven target detection, SLAM-based autonomous navigation, edge computing, and digital twins. These technologies transcend individual production links, exhibiting universality and transferability across both domains, thereby constituting critical enablers for comprehensive intelligence in smart ranch systems. The following analysis emphasizes the integration mechanisms between these generic technologies and the aforementioned specific scenarios, together with their cross-scenario transferability and application prospects.

5.1. Deep Learning-Driven Ranch Target Detection

The emergence of visual foundation models has opened new avenues for intelligent detection in ranch environments. The Segment Anything Model (SAM) achieves zero-shot segmentation through prompt engineering, thereby reducing data annotation costs for adaptation to novel scenarios. Research teams have already attempted to apply SAM to rapid segmentation of forage quality regions, achieving segmentation performance approaching that of fully supervised models under specific conditions.

Deep learning models deployed in ranch field environments are susceptible to interference from illumination variations, object occlusion, and on-site dust, leaving substantial scope for optimization in environmental adaptability and stability. An additional challenge confronting deep learning in ranch applications is the cost of data annotation. Compared with conventional agricultural scenarios, sample collection and annotation in ranch environments are considerably more challenging because livestock movement increases annotation difficulty, and forage exhibits substantial natural morphological diversity. The development of unsupervised and semi-supervised learning methods is expected to mitigate this constraint; specifically, pre-training on unannotated data can substantially reduce reliance on annotated samples. Rohan et al. [68] reported that publicly available ranch behavior recognition datasets currently total fewer than 20, most of which are small-scale (<5000 images)—far fewer than general target detection datasets such as COCO, which comprises over 330,000 images. The scarcity of annotated samples has emerged as the primary obstacle to the deployment of deep learning technologies in ranch scenarios. Figure 8 illustrates the deep learning-driven ranch target detection workflow, whereas Figure 9 presents the application scenarios and performance metrics of deep learning in smart ranch systems.

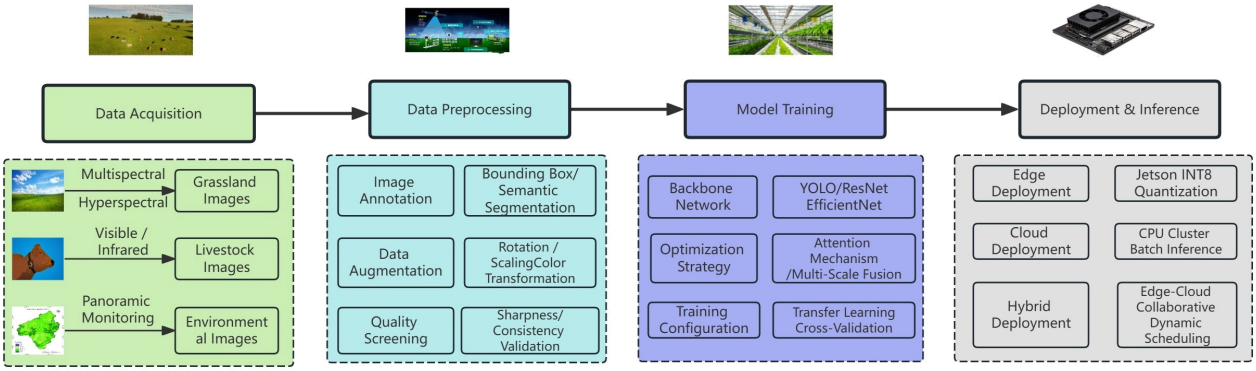

Figure 8. Deep learning-driven ranch target detection process. **Abbreviations:** YOLO = You Only Look Once; ResNet = Residual Network; EfficientNet = Efficient Network; INT8 = 8-bit Integer Quantization; CPU = Central Processing Unit.

5.2. Ranch SLAM Navigation and Autonomous Operation

Simultaneous Localization and Mapping (SLAM) was originally developed to enable autonomous robots to navigate unknown environments by concurrently constructing maps and tracking their positions within them [74]. In ranch contexts, where Global Navigation Satellite System (GNSS) signals may be degraded by dense vegetation, livestock housing structures, or topographic occlusion, and where pre-existing high-precision maps are rarely available, SLAM provides the foundational capability for robots and autonomous machinery to operate without human guidance across dynamic, unstructured terrain. Consequently, SLAM technology constitutes the core enabler for autonomous operation of ranch robots. A detailed comparison of SLAM navigation technologies for ranch robots is presented in Table 4.

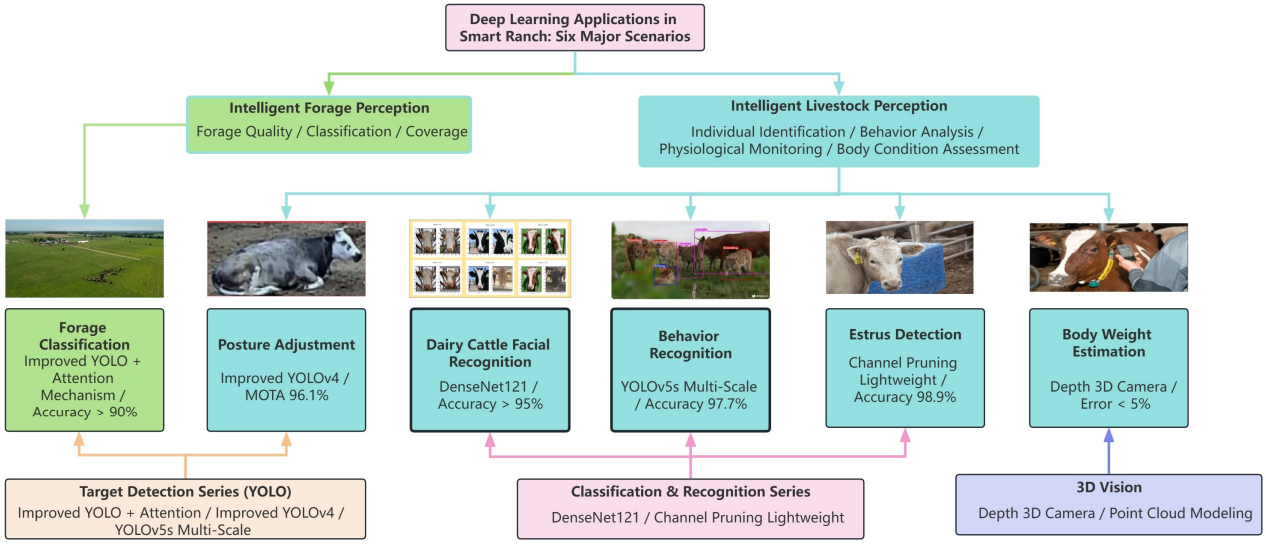

Figure 9. Application scenarios and performance indicators of deep learning in smart ranch. **Abbreviations:** YOLO = You Only Look Once; MOTA = Multiple Object Tracking Accuracy; IDF1 = Identification F1 Score; DenseNet121 = Densely Connected Convolutional Network 121.

Table 4. Comparison of ranch robot SLAM navigation technologies.

SLAM Type	Sensor Configuration	Mapping Algorithm	Localization Accuracy	Application Scenario	Advantages	Limitations	Ref.
LiDAR SLAM (2D)	Single/Dual 2D LiDAR + Odometry	Cartographer/ Gmapping	±2–5 cm	Structured Livestock Housing/ Corridor Navigation	Mature Algorithm/ Low Computational Cost	Lack of 3D Information/Feature Sparsity Degradation	[75]
Semantic SLAM	LiDAR/Vision + Semantic Segmentation	Semantic-Assisted Registration Framework	±2–5 cm	Dynamic Environment (Including Livestock Movement)	Dynamic Object Recognition for Enhanced Robustness	Semantic Segmentation Increases Computational Burden	[76]
Visual SLAM	Mono/ Stereo Camera + IMU	ORB-SLAM3/ VINS-Fusion	±3–10 cm	Indoor Precision Operation/ Texture-Rich Areas	Low Cost/Rich Information/ Compact Size	Light Sensitive/ Strong Texture Dependency	[77]
LiDAR-Vision Fusion	3D LiDAR + Depth Camera + IMU	Multi-Sensor Fusion Framework	±1–2 cm	Complex Dynamic/Ranch Environment	Complementary Sensor Information/Highest Robustness	System Complexity/Calibration Difficulty/High Cost	[78]
LiDAR SLAM (3D)	3D LiDAR + IMU + Odometry	LOAM/ LIO-SAM	±1–3 cm	Ranch Open Environment/ 3D Mapping	Rich 3D Information/ High Robustness	High Cost/Large Data Volume/ Computationally Intensive	[78]

Note: SLAM = Simultaneous Localization and Mapping; LiDAR = Light Detection and Ranging; IMU = Inertial Measurement Unit; GNSS = Global Navigation Satellite System; AMCL = Adaptive Monte Carlo Localization; ORB-SLAM3 = Oriented FAST and Rotated BRIEF Simultaneous Localization and Mapping 3; VINS-Fusion = Visual-Inertial Navigation System Fusion; LIO-SAM = Lidar Inertial Odometry Smoothing and Mapping; LOAM = Lidar Odometry and Mapping.

Regarding LiDAR-based SLAM, three-dimensional (3D) LiDAR systems utilize point cloud registration algorithms to achieve centimeter-level positioning accuracy. Song et al. [75] designed an autonomous navigation system for an intelligent push-feed robot in dairy barns based on LiDAR SLAM, employing the Cartographer algorithm for ranch envi-

ronment map construction, the Adaptive Monte Carlo Localization (AMCL) algorithm for robot localization, and the Dijkstra algorithm for work path planning. Experimental results demonstrated that the system achieved positioning deviations below 0.04 m in ranch environments, thereby verifying the feasibility of autonomous operation in such environments.

Owing to dynamic changes in forage scenarios—such as forage growth and livestock movement—semantic SLAM methods enhance system robustness through the identification and segmentation of dynamic objects. Lv et al. [76] fused ORB-SLAM2 with Mask R-CNN instance segmentation networks to achieve real-time removal of dynamic objects in agricultural scenarios, thereby improving SLAM stability in dynamic environments. Concerning visual SLAM, deep learning-based feature extraction methods exhibit superior matching robustness in repetitive texture scenarios—such as large-area grasslands—compared with traditional hand-crafted features. Tan et al. [77] developed a SLAM system based on an improved Cartographer framework for greenhouse environments with low-density canopies, enhancing localization accuracy under vegetation occlusion through adaptive point cloud registration strategies; these technologies are referable for ranch environment applications.

The multi-source fusion scheme integrating GNSS, inertial measurement unit (IMU), LiDAR, and vision represents the current mainstream technical route, achieving tight-coupled fusion through factor graph optimization frameworks and maintaining reliable localization even in GNSS signal-occluded areas. Thrun et al. [74] systematically elaborated on the theoretical foundation of multi-sensor fusion localization under the probabilistic robotics framework, a work that has become a classic textbook in the robotics field. Sun et al. [78] proposed a greenhouse autonomous walking system based on LIO-SAM mapping and LiDAR-vision fusion localization, achieving high-precision localization in complex environments; these technologies are referable for ranch environment applications. However, current SLAM applications in ranch environments remain limited to small-scale experimental scenarios, and critical issues—including global consistency map construction across tens to hundreds of square kilometers of large-area grasslands and cumulative drift suppression during long-term operation—have yet to be adequately resolved.

5.3. Edge Computing and Ranch Real-Time Decision-Making

Edge computing serves as the foundational enabler for real-time closed-loop control in smart ranch systems. Platforms such as the NVIDIA Jetson series can deploy deep learning models under stringent power constraints, achieving typical inference latencies below 50 ms. Model quantization techniques (e.g., INT8) and inference acceleration strategies can improve processing speed by several orders of magnitude while constraining precision loss to within 2% [79]. In livestock breeding scenarios, edge AI devices can simultaneously process multiple video streams, thereby enabling group-level behavior analysis. Tangorra et al. [80] reviewed IoT sensor applications in dairy cattle farming, emphasizing that the integration of edge computing and IoT represents an inevitable trend toward real-time ranch monitoring.

Edge computing offers distinct advantages in ranch environments. First, its low end-to-end transmission latency satisfies the stringent requirements for real-time equipment control. Second, the system uploads only anomalous data and statistical summaries, thereby significantly reducing network bandwidth consumption. Third, raw video data are processed locally, ensuring data privacy. Finally, critical functions remain operational during network interruptions. In ranch scenarios with limited network infrastructure, these advantages are particularly pronounced. Conventional cloud computing solutions necessitate the upload of large video datasets to remote platforms for processing, imposing substantial bandwidth demands that are impractical to satisfy in remote ranches with

constrained connectivity [81]. Alonso et al. [81] designed an Edge-IoT intelligent monitoring platform tailored for dairy cattle breeding scenarios, achieving real-time monitoring of livestock and crops through localized edge-node processing. These results verify the feasibility of edge computing in ranch applications.

Liu et al. [82] systematically reviewed advances in intelligent control technologies for agricultural equipment, identifying edge intelligence as a critical future direction. The synergistic integration of edge computing with sensor networks and wireless communication can establish a complete closed loop from perception through decision-making to execution, thereby enabling truly intelligent management. Nevertheless, the primary challenges confronting edge computing in ranch applications include limited computational capacity and stringent power constraints, necessitating trade-offs between model precision and inference speed. Furthermore, the extreme temperature ranges (−40 °C to 60 °C) characteristic of ranch environments impose rigorous requirements on thermal dissipation and operational stability of edge devices. Industrial-grade variants of commercial edge computing platforms typically cost three to five times more than their consumer-grade counterparts, thereby limiting large-scale deployment. The architecture for edge computing-enabled real-time decision-making in smart ranch systems is illustrated in Figure 10.

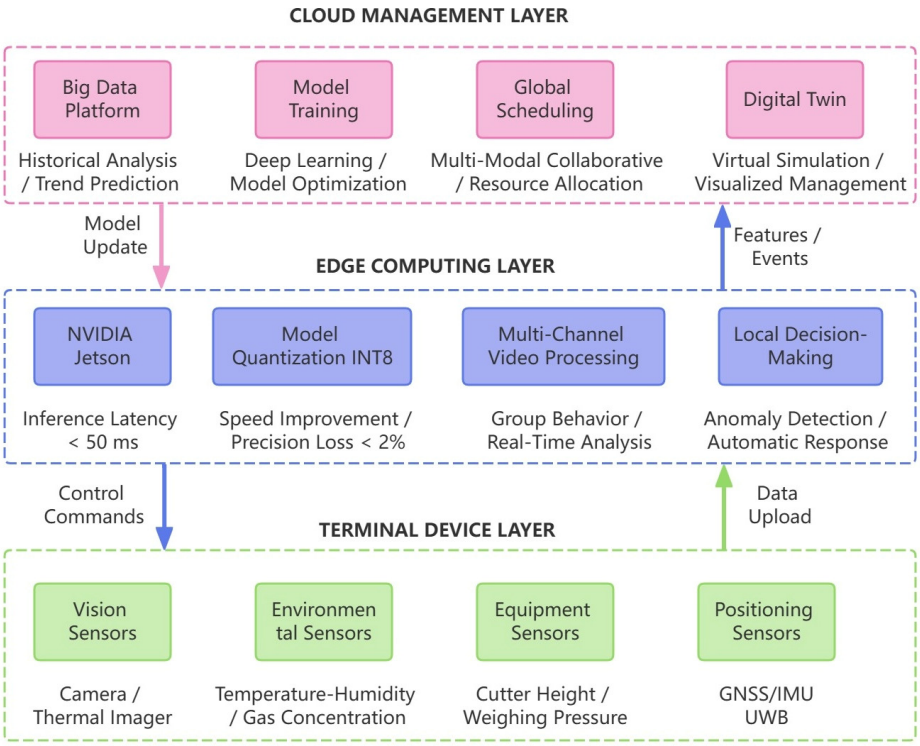

Figure 10. Edge computing and smart ranch real-time decision-making architecture. **Abbreviations:** INT8 = 8-bit Integer Quantization; GNSS = Global Navigation Satellite System; IMU = Inertial Measurement Unit; UWB = Ultra-Wideband.

5.4. Digital Twins and Ranch Virtual-Real Fusion

Digital twin technology enables bidirectional coupling between physical and virtual ranch environments through the construction of high-fidelity digital replicas. At the geometric level, three-dimensional ranch models with centimeter-level precision can be constructed via unmanned aerial vehicle (UAV) oblique photogrammetry and LiDAR scanning. At the physical level, real-time multi-source sensor data drive the synchronous updating of digital replicas to mirror the status of physical ranch systems. At the behavioral level, predictive capabilities are realized through mechanistic models, including crop growth and livestock nutrition models. Verdouw et al. [83] reviewed digital twin applications in

smart agriculture, highlighting their substantial potential for virtual simulation, remote monitoring, and predictive maintenance.

Applications of digital twins in smart ranch systems encompass virtual simulation and scenario optimization, remote monitoring and visual management, predictive maintenance, and personnel training. Currently, digital twin implementation for ranch operations remains at the demonstration and exploratory stage; achieving high model fidelity and real-time synchronization constitutes a critical technical hurdle. Compared with conventional monitoring approaches, digital twins offer the distinct advantage of comprehensive operational visualization, allowing management personnel to intuitively comprehend real-time ranch conditions through digital replicas and to conduct virtual scenario optimization. Nasirahmadi et al. [84] proposed a next-generation agricultural digitalization framework based on the digital twin paradigm, emphasizing that multi-scale modeling—from individual livestock to the entire ranch—and real-time data assimilation represent core challenges for realizing high-fidelity digital twins.

The implementation of digital twin technology necessitates multidisciplinary collaboration: three-dimensional modeling provides the geometric foundation, sensor networks furnish real-time data streams, mechanistic models enable behavioral simulation, and cloud computing platforms deliver the requisite computational resources. For ranch systems, which are inherently complex, the efficient integration of these technologies while simultaneously ensuring model fidelity and real-time performance remains a primary challenge confronting both researchers and practitioners. Moreover, the substantial costs associated with platform construction and subsequent operation and maintenance currently limit the practical applicability of digital twins to large-scale intensive ranches; lightweight, cost-effective solutions tailored for small and medium-sized ranches remain under active investigation. The digital twin framework for smart ranch systems is illustrated in Figure 11.

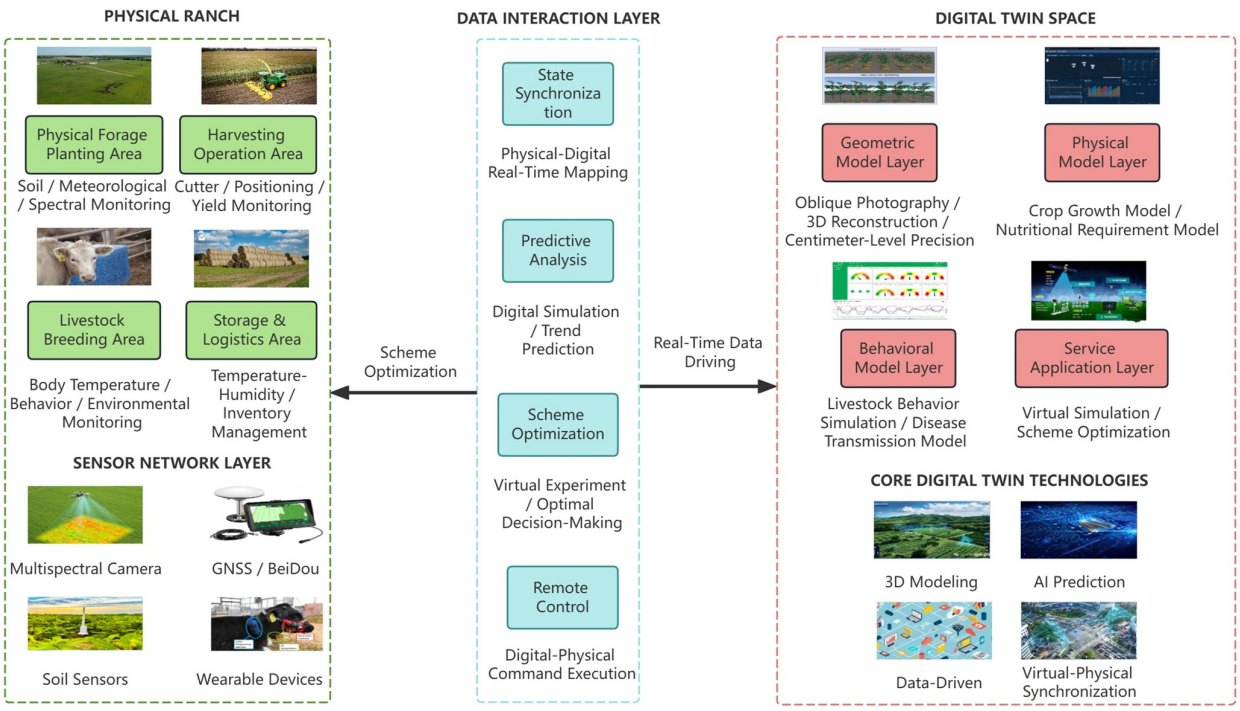

Figure 11. Digital twin and smart ranch twin framework. **Abbreviations:** UAV = Unmanned Aerial Vehicle; GNSS = Global Navigation Satellite System; BeiDou = BeiDou Navigation Satellite System; AI = Artificial Intelligence.

5.5. Cross-Scenario Integration: Forage–Livestock Coupled Perception

The preceding sections have treated forage harvesting and intelligent livestock farming as two independent modules, each equipped with its own sensor suite and decision pipeline. Yet the defining feature that distinguishes a smart ranch from conventional agricultural perception systems is not the sophistication of either module in isolation, but the dynamic coupling between them: real-time perception of forage supply must be matched to real-time perception of livestock demand, and the resulting decisions must flow bidirectionally across the two modules. This section articulates the mechanisms, current gaps, and future requirements of this forage–livestock coupled perception paradigm.

The coupled perception loop operates through three principal data linkages. First, forage quality sensing—via multispectral and hyperspectral imaging (Section 3.1)—generates spatially explicit crude-protein, neutral detergent fiber (NDF), and acid detergent fiber (ADF) maps that feed directly into individual livestock nutritional-requirement models (Section 4.1), thereby enabling dynamic total mixed ration (TMR) formulation rather than static recipes. Second, livestock health and behavior monitoring—using wearable accelerometers and thermal imaging (Sections 4.2 and 4.3)—detects stress, disease, or estrus events that alter feed intake patterns; these anomalies trigger automatic recalculation of the forage harvest schedule to ensure that sufficient high-quality feed is available when demand spikes. Third, environmental sensing—encompassing soil moisture and meteorological monitoring (Section 2.1)—drives forage growth models that predict biomass and maturity windows; the predicted supply curve is subsequently cross-referenced against livestock population growth models to optimize stocking density and culling decisions months in advance. In each linkage, the sensor network serves not merely as a data source for a single module, but as a node in a ranch-wide digital nervous system.

Despite its conceptual appeal, forage–livestock coupled perception remains largely unrealized in practice. Complete end-to-end practical demonstrations on real-world grassland ranches are extremely scarce, impeded by three core engineering barriers: (i) heterogeneous spatiotemporal data alignment, (ii) insufficient coupled mechanism models, and (iii) edge–cloud collaborative optimization under asymmetric massive data streams. The two modules currently operate on incompatible data standards: forage-quality spectral data are stored in raster geospatial formats (GeoTIFF, ENVI) with meter-level spatial resolution, whereas livestock individual records are maintained in relational databases (SQL, NoSQL) with minute-level temporal resolution. No unified middleware yet exists to align these heterogeneous spatiotemporal granularities into a common decision frame. Moreover, the mechanism models that would translate forage supply forecasts into livestock nutritional plans—such as dynamic ration-balancing algorithms that account for real-time forage variability—are underdeveloped; most precision-feeding systems still rely on preset recipes that ignore the spatial heterogeneity of pasture quality revealed by UAV remote sensing. Consequently, the "smart" in smart ranch has so far been confined to module-level automation rather than system-level optimization.

Closing this gap requires three concurrent advances. (i) Standardized data-exchange protocols—building on existing agricultural IoT frameworks such as GB/T 41187–2021 [85]—must be extended to specify spatiotemporal alignment rules for forage raster data and livestock temporal records. (ii) Coupled mechanistic models, integrating crop growth simulation (e.g., APSIM, DSSAT) with livestock nutrition models (e.g., NRC, CNCPS), must be developed and validated under grassland pastoral conditions. (iii) Edge–cloud collaborative architectures must be designed to handle the asymmetric data loads: high-volume spectral imagery from forage fields and high-frequency sensor streams from livestock, converging on a unified decision node that generates harvest plans, feeding schedules, and stocking recommendations in a single optimization run. Only when these

cross-module linkages are established will a smart ranch transcend the sum of its parts and realize the closed-loop intelligent management that its name implies.

6. Discussion

6.1. Current Major Challenges

From both fundamental theoretical and industrial-application perspectives, the development of smart-ranch sensing and intelligent-perception technologies confronts four interrelated challenges:

To systematically illustrate performance gaps across the three tiers of technology maturity, Table 5 synthesizes cross-study comparisons of representative sensing and perception technologies under laboratory, field, and commercial-deployment conditions. The data reveal a consistent pattern: laboratory metrics are promising, field deployment incurs significant degradation, and commercial-scale application remains limited for most emerging technologies.

Table 5. Cross-study performance comparison across laboratory, field, and commercial deployment tiers.

Technology/Metric	Laboratory/ Controlled Conditions	Field/Actual Ranch Conditions	Commercial Deployment Status	Key Performance Gap	Ref.
Intelligent cutting platform (harvesting loss reduction)	10–20% reduction	6–14% reduction (estimated with 20–40% degradation)	Limited deployment; reliability issues	Accuracy degradation 20–40% under dust/ vibration	[33,34,86]
Hyperspectral forage quality inversion (crude protein, R^2)	0.90–0.95	0.60–0.80 (under variable illumination/ cloud)	Not yet deployed for on-the-go detection	Illumination sensitivity; poor model transferability	[19,30,87]
Livestock behavior recognition (deep learning accuracy)	>90%	65–75% (15–25 percentage points lower)	Pilot trials only; dataset scarcity	Generalization bottleneck; annotation cost	[68]
Sensor reliability (MTBF)	5000+ h (indoor industrial)	<500 h (dust, vibration, extreme temperatures)	Below threshold for profitable large-scale operation	Environmental robustness; extreme climate adaptation	[86]
SLAM autonomous navigation (positioning deviation)	<0.04 m (dairy barn)	Untested at >10 km^2 grassland scale	Demonstration/ pilot stage	Large-area drift; dynamic object interference	[74,75]
TMR precision feeding (ingredient accuracy)	±1–3%	±3–5%	Deployed in intensive dairy/ pig farms	Adaptation to grazing + supplementary feeding model	[56,88]

Note: MTBF = Mean Time Between Failures; R^2 = Coefficient of Determination; TMR = Total Mixed Ration; SLAM = Simultaneous Localization and Mapping; GNSS = Global Navigation Satellite System; IMU = Inertial Measurement Unit.

These quantitative gaps reflect deeper theoretical and systemic challenges, analyzed below. Three trends emerge from this comparison. First, the laboratory-to-field performance gap is pervasive: forage-harvesting sensors suffer 20–40% accuracy degradation under dust and vibration [86], hyperspectral models lose 10–35 percentage points under variable illumination [87], and behaviour-recognition accuracy declines by 15–25 percentage points in complex ranch environments [68]. Second, most emerging technologies remain at pilot or demonstration stage; only TMR feeding has achieved commercial maturity, yet it is confined to intensive systems and lacks adaptation to grassland-pastoral conditions [88]. Third, sensor reliability (mean time between failures, MTBF) constitutes a severe bottleneck: the tenfold drop from 5000 h to <500 h under ranch conditions di-

rectly determines economic viability [86]. Closing this generalization gap will require, in the authors' view, a coordinated multi-ranch benchmark initiative involving at least ten geographically dispersed ranches, standardised environmental logging, and a public leaderboard with held-out test sets—an effort estimated at 2–3 years and US$1.5–2.0 million based on typical EU–US agricultural R&D programme costs—yet no funding programme currently targets this specific need [88].

At the algorithmic and theoretical level, multi-modal fusion frameworks remain inadequately adapted to complex ranch environments. Grassland illumination is inherently variable, airborne dust is abundant, rain and snow are frequent, and target occlusion is commonplace; existing perception algorithms are predominantly developed for ideal environments and exhibit insufficient field operational stability. Existing computer-vision and spectral-perception theories are largely developed under ideal imaging conditions. Consequently, systematic theoretical guarantees for perception robustness in complex ranch environments—characterized by variable illumination, airborne dust, and frequent weather extremes—remain largely absent. For instance, forage hyperspectral imaging is highly sensitive to cloud occlusion and solar-elevation-angle variations, whereas the detection mechanisms underpinning livestock behaviour recognition under low-light, backlit, and multi-animal-occlusion conditions remain poorly understood.

Cross-scenario model generalization represents a second theoretical bottleneck. Existing deep-learning models depend on large-scale annotated datasets, yet different ranches vary significantly in livestock species, breeds, growth stages, and feeding methods. The generalization mechanisms governing model transfer from laboratory to field, and from single-ranch to cross-domain deployment, remain unestablished. He et al. [26] observed that current intelligent-perception research in precision livestock farming is predominantly designed for specific scenarios and lacks adaptive theoretical frameworks oriented toward open environments. Rohan et al. [68] reported that behavioural-recognition accuracy under laboratory conditions typically exceeds that in actual ranch environments by 15–25 percentage points. As shown in Table 5, this 15–25 percentage-point accuracy drop from laboratory to field conditions, together with limited model generalization, constitutes a core theoretical bottleneck that urgently demands resolution.

Dynamic fusion of multi-source heterogeneous information remains theoretically elusive. Forage harvesting and livestock breeding generate heterogeneous data spanning multispectral and hyperspectral imagery, temporal sensing streams, and spatial-positioning information, which differ fundamentally in temporal–frequency characteristics, spatial resolution, and semantic granularity. Zhai et al. [15] noted that multi-sensor information fusion requires theoretical breakthroughs in heterogeneous data spatiotemporal alignment, uncertain-information quantification, and multi-scale dynamic fusion. Nevertheless, cross-modal fusion frameworks for forage–livestock coupled systems remain virtually non-existent. Edge intelligence and real-time decision-making are similarly constrained. Ranch operations impose strict closed-loop latency requirements on perception–decision–execution cycles (e.g., autonomous-navigation responses below 100 ms). Yet how to achieve collaborative optimization of high-precision inference and low-latency decision-making under edge-node constraints on computing power, energy consumption, and bandwidth remains a key scientific problem for edge-computing theory in ranch applications [76].

From a systems-integration and standardization perspective, unified protocols for multi-source heterogeneous data fusion remain undeveloped. Smart-ranch systems ingest heterogeneous data from multispectral and hyperspectral imaging, LiDAR point clouds, temporal sensing streams, and spatial-positioning information. These sensors differ fundamentally in sampling frequency (soil sensors: 10–30 min intervals versus IMU: >100 Hz), temporal benchmarks, and spatial coordinate systems; consequently, technical frameworks

for data alignment and spatiotemporal registration remain fragmented [15]. The data models characterising forage harvesting and livestock breeding differ markedly—the former emphasising spatial-distribution modelling, the latter time-series analysis—leaving cross-domain data-fusion interfaces and technical specifications in an undeveloped state. Multi-machine coordinated communication and control protocols also require refinement. Whole-process forage harvesting involves coordinated operation of multiple equipment types—mowers, tedders, balers, and transport vehicles—yet unified communication protocols and coordinated control standards for heterogeneous ranch equipment groups remain unavailable. Technical specifications for protocol adaptation, latency guarantees, and reliability enhancement for CAN (Controller Area Network) bus, 5G-V2X (5G vehicle-to-everything), and other communication technologies in ranch environments remain incomplete [41].

A comprehensive smart-ranch standard system is likewise absent. Sensor interface protocols, data formats, and performance-testing methods lack unified standards, creating interoperability barriers between equipment from different manufacturers. Currently, only a limited number of industry standards exist for agricultural IoT (e.g., GB/T 41187–2021, *Agricultural Internet of Things Application Services*) [85]. Standard systems specifically targeting smart-ranch perception technology, data fusion, and system evaluation remain nascent [85]. Establishing full-chain technical standards covering sensing-data acquisition, processing, fusion, and application is therefore essential to provide institutional guarantees for large-scale technology adoption.

Hardware capabilities also exhibit marked deficiencies. Domestic self-sufficiency in high-end sensing core devices remains low. High-precision GNSS boards, solid-state LiDAR, hyperspectral imaging chips, and other core sensors still rely primarily on imports, with localisation rates below 30%. This entails not only high costs—typically three to five times those of domestic equivalents—but also supply-chain security risks [89]. Extreme-environment adaptability is similarly inadequate. Complex ranch environments pose severe challenges to sensor reliability: high-cold pastoral areas with low temperatures and strong winds (winter temperatures below −40 °C), southern regions with high rainfall and humidity (relative humidity > 90%), and grasslands with weak grid power and no network connectivity, all leading to sensor-performance degradation and communication interruption. Sensor performance degradation under extreme temperature and high-humidity conditions has not been fully resolved, as evidenced by low mean time between failures (MTBF < 500 h) under field conditions (see Section 2.1.5).

Northern cold-dry pastoral regions—where winter temperatures fall below −40 °C and frozen-soil layers reach 1.5–2.0 m—are not merely climatic footnotes; they impose specific, quantifiable degradation mechanisms on every sensor category described above. For electrochemical and battery-powered sensors—soil-moisture probes, wearable accelerometers, and ear-tag temperature loggers—lithium-ion capacity degrades by 40–60% at −20 °C, while internal resistance doubles, causing voltage sag that triggers premature shutdown below the rated cutoff. At −40 °C, most commercial Li-ion cells cease functioning entirely [90,91], yet the industry continues to specify operating temperatures of −20 °C to +60 °C without acknowledging that northern pastoral winters exceed this lower bound by 20 °C. For optical sensors—multispectral cameras, hyperspectral imagers, and LiDAR—thermal shock between −40 °C and +60 °C induces differential expansion in lens mounts, degrading calibration and optical alignment. Moreover, lens-surface frosting under extreme cold blocks optical transmission in the visible and near-infrared bands, while existing anti-fog coatings are designed for humid (not arid) cold and lose effectiveness when dust particles provide nucleation sites for ice crystals. For MEMS inertial sensors—IMUs in cutting-platform levelling and accelerometers in wearable collars—temperature-dependent

bias drift (typically 0.01–0.05 °/s/°C for gyroscopes and 1–5 mg/°C for accelerometers) accumulates over the 65 °C annual temperature swing, causing attitude-estimation errors that exceed the ±1 cm cutting-height accuracy requirement after only 10–15 min of operation without real-time temperature compensation [92,93]. Existing "solutions"—such as commercial heated enclosures for cameras and insulated battery boxes—impose substantial mass and power penalties, are rarely validated below −30 °C, and ignore freeze–thaw cycling that cracks potting compounds and severs solder joints [94,95]. In short, the sensor industry has yet to develop a coherent design philosophy for cold-dry pastoral environments. Current products are either temperate-climate devices with marginal derating or military-grade hardware with prohibitive cost, leaving a critical gap for purpose-built, ranch-validated, wide-temperature-range sensor systems.

Techno-economic constraints further impede adoption. Unit prices for hyperspectral imaging equipment are typically 5–10 times those of multispectral cameras; livestock wearable sensors cannot simultaneously achieve high-frequency sampling (>1 Hz) and long endurance (>several weeks); and improvements in edge-computing-node processing power conflict with power-consumption control. Identifying optimal techno-economic configurations for ranches of varying scales therefore remains a critical barrier to transitioning smart-ranch technology from demonstration to widespread adoption.

Field investigations in Inner Mongolian grassland pastoral areas and synthesis of Chinese agricultural industry statistics [96,97], unless otherwise cited. The techno-economic literature on smart ranches is dominated by cost–benefit analyses of intensive systems in developed countries (e.g., 1000-head dairy barns in the Netherlands or Israel), which typically assume grid electricity, broadband connectivity, and amortisation periods of 5–7 years [97]. These assumptions are largely inapplicable to northern grassland pastoral areas in China, where most ranches operate at small-to-medium scale (<200 head), experience seasonal grid-power shortages in remote regions, and face payback-period requirements below three years due to limited access to agricultural credit [96]. Existing studies proposing "optimal techno-economic configurations" for ranches of different scales often rely on linear-programming models with fixed input prices, yet overlook forage-price volatility (approximately ±30% year-on-year due to drought) and the seasonality of livestock cash flow (concentrated in autumn slaughter periods). These factors can substantially reduce the operational validity of static optimization models. Achieving economically viable smart-ranch technology for small-to-medium pastoral operations will require not merely incremental cost reduction, but a fundamental rethinking of business models—specifically, sensor-as-a-service (SaaS) leasing with bundled maintenance, and government-subsidy structures that front-load capital costs rather than reimbursing post-purchase expenditure. To our knowledge, no peer-reviewed study has yet modeled these alternative financing mechanisms under Chinese pastoral credit constraints, leaving a critical gap between technical possibility and economic reality.

6.2. Future Development Trends

Based on current technology-evolution trajectories and industrial-development demands, future smart-ranch sensing-technology development will exhibit five converging trends.

First, domestic sensor substitution will continue to accelerate (bottleneck severity: high; TRL 3–4; estimated timeline: 3–5 years). The domestic-production share of major agricultural sensors is projected to rise from <30% to >50% by 2030, accompanied by corresponding price reductions of 30–50% [98]. Nevertheless, breakthroughs in precision, long-term stability, and environmental adaptability remain essential; without them, displacing imported high-end products will prove challenging.

Second, multimodal-perception fusion will evolve toward **prioritizing standardization and plug-and-play interoperability** (bottleneck severity: high; TRL 2–3; estimated timeline: 2–4 years). Multisensor-fusion architectures built upon open interfaces—such as OPC UA and MQTT—and unified middleware will substantially lower integration complexity [99,100].

Third, edge intelligence and cloud–edge collaborative applications will see progressive deployment (bottleneck severity: moderate; TRL 5–6; estimated timeline: 1–2 years for grid-connected scenarios; 3–5 years for off-grid scenarios) [101]. In grid-connected intensive dairy barns, NVIDIA Jetson-class platforms are already deployable; conversely, off-grid northern pastoral regions require hybrid lithium–titanate (LTO) battery systems with active thermal management before edge-AI rollout becomes viable.

Fourth, digital twins will transition from demonstration to scaled application (bottleneck severity: low; TRL 2–3; estimated timeline: 5–8 years) [102]. Rather than pursuing full-scale twin construction, ranch operators should adopt a phased approach beginning with "digital shadow" implementations—automated three-dimensional reconstruction coupled with streamlined dashboard visualization of sensor data—before advancing to predictive simulation.

Finally, comprehensive unmanned operation will advance incrementally. On large-scale ranches, unmanned forage harvesting and feeding management will first be realized in constrained scenarios—such as nocturnal push-feeding and fixed-route feeding—whereas fully autonomous operation demands further technological maturation. From a near-term perspective (3–5 years), assisted driving (automatic navigation with human oversight) and teleoperated control represent realistic targets. Medium-to-long-term goals (5–10 years) encompass autonomous operation under bounded conditions, while comprehensive unmanned operation remains a long-term vision (>10 years).

7. Conclusions

This paper has comprehensively reviewed the application status and development directions of advanced sensing and intelligent-perception technologies across the two core scenarios of smart-ranch operations, yielding the following conclusions.

Forage harvesting: The technological framework for whole-process forage-harvesting sensing has been preliminarily established yet remains far from mature deployment. Multispectral and hyperspectral imaging can be employed for forage-quality detection; hyperspectral-based predictive models for crude-protein content have achieved coefficients of determination (R^2) exceeding 0.90. Automatic cutting-platform height-control systems can reduce harvesting losses by 10–20%, while intelligent scheduling systems enhance harvest efficiency and lower energy consumption. Nevertheless, the aforementioned performance data predominantly derive from laboratory or idealised field conditions. Precision degradation of 20–40% and sensor-reliability constraints (MTBF < 500 h) under actual ranch conditions (Table 5) have yet to be adequately resolved.

Livestock production: Perception technologies for intelligent livestock farming are advancing rapidly, yet coverage across species remains highly uneven. Deep-learning-based livestock-behaviour recognition can achieve accuracies above 90% under experimental conditions, with improved DeepSORT methods attaining MOTA of 96.1% and IDF1 of 98.0%. Multi-indicator fusion-based health early-warning systems enable early disease detection, and sensor-feedback-based intelligent ventilation and temperature-control systems can effectively improve the livestock-housing environment, reducing energy consumption by 20–30% relative to timed-ventilation modes. Existing research, however, is disproportionately focused on two intensively farmed species—pigs and dairy cattle. By contrast, studies on behaviour recognition for beef cattle, sheep, and other major herbivorous livestock

species in China remain remarkably inadequate. According to 2024 statistics published by Rohan et al. [68], the number of publicly available ranch behaviour-recognition datasets remains below 20, most comprising fewer than 5000 images—far smaller than general object-detection datasets. Data scarcity has therefore become a critical bottleneck constraining scalable deployment of deep learning in ranch behaviour recognition.

Emerging technologies: SLAM-based autonomous navigation, edge computing, real-time decision-making, and digital-twin-enabled cyber-physical fusion are increasingly penetrating ranch operations, laying the technical groundwork for next-generation smart-ranch development. The application of LiDAR SLAM in dairy-barn push-feed robots has verified the feasibility of autonomous operation in ranch environments, achieving positioning deviations below 0.04 m. Edge computing offers significant advantages for network-independent operation in remote ranches, while digital twins provide a new paradigm for visual ranch management. These technologies, however, currently remain predominantly at the proof-of-concept or pilot stage. Engineering challenges—including long-term operational stability in large-area grassland scenarios, adaptability to extreme environments, and economic feasibility—still demand breakthroughs.

Persistent challenges: Domestic production rates for core sensing devices remain below 30%, while insufficient adaptability to complex environments and the absence of unified data-fusion standards continue to impede progress. Of particular concern, the alpine, arid, and weak-grid conditions of northern grassland pastoral areas in China—notably the Inner Mongolia region—impose distinct requirements on sensor technology. Existing research has predominantly targeted temperate farmland or enclosed livestock housing. For the semi-open and fully open shed structures commonly employed in northern Chinese grassland pastoral areas, and under special conditions including wide seasonal temperature swings (winter −30 °C to summer 35 °C), the measurement ranges and precision specifications of existing sensors fall short of requirements. Research on dedicated sensor solutions for cold-dry regions and open livestock housing remains virtually non-existent. Future work should therefore prioritize cold-dry-environment sensor validation, off-grid edge-AI power solutions, and low-cost systems suited to the scale and credit constraints of Chinese small-to-medium-scale pastoral enterprises.

Limitations and outlook: This review synthesizes publicly available literature. Some performance data presented herein were obtained under standard laboratory conditions; consequently, the practical performance of these devices in real-world, complex pasture environments may deviate appreciably. Moreover, smart-ranch development constitutes an interdisciplinary research domain, and this review cannot exhaust all sub-disciplines. Further investigations may be pursued from the perspectives of animal husbandry, veterinary medicine, grassland ecology, and allied fields. In view of prevailing industry bottlenecks, follow-up research should prioritize four directions: (i) developing low-cost, dedicated sensors adapted to alpine pastoral areas; (ii) constructing cross-species, general-purpose datasets for animal-behaviour recognition; (iii) establishing industrial standards for sensing equipment and data formats; and (iv) exploring lightweight digital-twin solutions tailored to small- and medium-sized pastures.

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References

1. OECD; FAO. *OECD-FAO Agricultural Outlook 2022–2031*; OECD Publishing: Paris, France, 2022.
2. National Bureau of Statistics of China. *Statistical Communiqué of the People's Republic of China on the 2025 National Economic and Social Development*; China Statistics Press: Beijing, China, 2026.
3. Ministry of Natural Resources of China. *China Natural Resources Bulletin 2024*; Ministry of Natural Resources: Beijing, China, 2025.
4. Wang, S.; Li, H.; Zhang, H.; Ding, L.; He, C.; Sun, A.; Mao, X.; Song, J. Research on internal forced stage alfalfa bale drying processing technology. *For. Mach. Woodwork. Equip.* **2024**, *52*, 72–78. (In Chinese) [CrossRef]
5. Ministry of Agriculture and Rural Affairs of China. *China Agricultural Industry Development Report 2021*; China Agriculture Press: Beijing, China, 2021.
6. Farmers' Daily. How to Bridge the 74% "Digital Divide" in Smart Animal Husbandry. Available online: https://www.farmer.com.cn/2026/06/16/wap_991021489.html (accessed on 20 June 2026).
7. Central Committee of the Communist Party of China; State Council. Opinions on Further Deepening Rural Reform and Solidly Advancing Comprehensive Rural Revitalization. Available online: https://www.gov.cn/gongbao/2025/issue_11906/202503/content_7011166.html (accessed on 20 June 2026).
8. Central Committee of the Communist Party of China; State Council. Opinions on Anchoring Agricultural and Rural Modernization and Solidly Advancing Comprehensive Rural Revitalization. Available online: https://www.gov.cn/gongbao/2026/issue_12566/202602/content_7057938.html (accessed on 20 June 2026).
9. Xiong, B.; Sha, Y.; Song, H. *Research Progress of China's Intelligent Animal Husbandry During the "14th Five-Year Plan" Period*; China Agricultural Science and Technology Press: Beijing, China, 2026.
10. Cheng, M.; Yuan, H.; Cai, Z.; Wang, J.; Zhu, J.; Zhang, H.; Zhao, C. Research progress on high-throughput phenotypic information acquisition and analysis technology for field crops. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 314–324. (In Chinese) [CrossRef]
11. Walter, A.; Finger, R.; Huber, R.; Buchmann, N. Smart farming is key to developing sustainable agriculture. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 6148–6150. [CrossRef]
12. Zhang, X.; Chen, M.; Hu, X.; Li, S.; Song, X.; Rao, J. Review of hyperspectral and multispectral image fusion technology. *J. Sichuan Univ. Sci. Eng. (Nat. Sci. Ed.)* **2025**, *38*, 17–28. (In Chinese)
13. Yuan, L.; Li, W.; Yue, J.; Li, Z.; Zhao, Y.; Li, Q.; Feng, W.; Kou, G. A review of cattle behavior recognition methods based on computer vision and deep learning. *Smart Agric. Technol.* **2026**, *14*, 101867. [CrossRef]
14. Fogarty, E.; Swain, D.; Cronin, G.; Trotter, M. A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework. *Anim. Welf.* **2019**, *28*, 407–420. [CrossRef]
15. Zhai, C.; Yang, S.; Wang, X.; Zhang, C.; Song, J. Research status and prospects of intelligent measurement and control technology for agricultural machinery equipment. *Trans. Chin. Soc. Agric. Mach.* **2022**, *53*, 1–20. (In Chinese) [CrossRef]
16. Kalaji, H.M.; Bąba, W.; Gediga, K.; Goltsev, V.; Samborska, I.A.; Cetner, M.D.; Dimitrova, S.; Piszcz, U.; Bielecki, K.; Karmowska, K.; et al. Chlorophyll fluorescence as a tool for nutrient status identification in rapeseed plants. *Photosynth. Res.* **2018**, *136*, 329–343. [CrossRef]
17. Lyu, X.; Li, X.; Dang, D.; Dou, H.; Wang, K.; Lou, A. Unmanned Aerial Vehicle (UAV) remote sensing in grassland ecosystem monitoring: A systematic review. *Remote Sens.* **2022**, *14*, 1096. [CrossRef]
18. Qi, H.M.; Yang, X.C. Estimation of crude protein content in natural pasture grass using unmanned aerial vehicle hyperspectral data. *Comput. Electron. Agric.* **2024**, *221*, 109714. [CrossRef]

19. Gao, R.; Li, Z.; Ma, Z.; Kong, Q.; Rizwan, M.; Su, Z. Detection of forage crude protein content based on hyperspectral imaging. *Spectrosc. Spectr. Anal.* **2019**, *39*, 3245–3250. Available online: https://www.gpxygpfx.com/CN/10.3964/j.issn.1000-0593(2019)10-3245-06 (accessed on 23 August 2026). (In Chinese)
20. Yu, L.; Gao, W.; Shamshiri, R.; Wang, J.; Li, P.; Zhao, Y. Research progress of soil moisture sensors. *Agric. Eng. Technol.* **2021**, *41*, 87. (In Chinese) [CrossRef]
21. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of remote sensing in precision agriculture: A review. *Remote Sens.* **2020**, *12*, 3136. [CrossRef]
22. *IEC 60751*; Industrial Platinum Resistance Thermometers and Platinum Temperature Sensors. International Electrotechnical Commission: Geneva, Switzerland, 2008.
23. Xiao, D.; Lin, S.; Liu, Q.; Huang, Y.; Zeng, R.; Chen, L. Automatic pig ear temperature extraction algorithm based on infrared thermal imaging. *Trans. Chin. Soc. Agric. Mach.* **2021**, *52*, 196–204. (In Chinese) [CrossRef]
24. Lee, M.; Seo, S. Wearable wireless biosensor technology for monitoring cattle: A review. *Animals* **2021**, *11*, 2779. [CrossRef]
25. Li, L.; Liu, Z.; Zhao, X.; Li, S. Individual behavior monitoring and recognition of caged breeding chickens based on accelerometer sensors. *Trans. Chin. Soc. Agric. Mach.* **2019**, *50*, 247–254. (In Chinese) [CrossRef]
26. He, D.J.; Liu, D.; Zhao, K.X. Research progress in intelligent animal information perception and behavior detection in precision animal husbandry. *Trans. Chin. Soc. Agric. Mach.* **2016**, *47*, 231–244. (In Chinese) [CrossRef]
27. Lian, J.; Sun, K.; Zhu, W.; Yin, R.; Han, Y.; Li, H. Research on poultry health management system based on intelligent inspection robot. *Shandong Agric. Sci.* **2019**, *51*, 152–155. (In Chinese) [CrossRef]
28. Song, Y.; Wan, J.; Guo, X.; Zhang, J.; Wang, Y. Characteristics and recovery of ammonia from pig barns during the growing and fattening period. *Chin. J. Environ. Eng.* **2026**, *20*, 867–877. Available online: https://kns.cnki.net/kcms2/article/abstract?v=hH4QDuxDhLQK_WyYCRUBaW-0mthzyogsNUYMzOx-JhpvBmYQj_nVyXwf_mM0kwaNU4RRaQ7dDDd-vdXmlGWVBawdASe0jGvb3AuH9tn5B02OlubLc_XbnAHa4_l2t6LJgGzUovSZB_VGRsvv2hoIxxTb4rj7MJJPJ3JLVJ7p_0cgsqqsPd6UEQ==&uniplatform=NZKPT&language=CHS (accessed on 23 August 2026). (In Chinese)
29. Zheng, Y.; Hui, X.; Cai, D.; Shoukat, M.R.; Wang, Y.; Wang, Z.; Ma, F.; Yan, H. Calibrating ultrasonic sensor measurements of crop canopy heights: A case study of maize and wheat. *Front. Plant Sci.* **2024**, *15*, 1354359. [CrossRef]
30. Jin, C.; Cai, Z.; Ni, Y.; Li, H.; Zhang, L. Review of online yield monitoring for grain combine harvesters. *J. China Agric. Univ.* **2020**, *25*, 137–152. (In Chinese) [CrossRef]
31. Du, X.; Wang, X.; Chai, S.; Liu, X. Quantitative analysis of natural forage nutritional components by near-infrared spectroscopy. *Chin. Agric. Sci. Bull.* **2015**, *31*, 6–11. (In Chinese)
32. Chen, H.; Han, Y.; Feng, L.; Li, M. Application of smart agriculture in cotton production management. *Cotton Sci.* **2020**, *32*, 269–278. (In Chinese) [CrossRef]
33. Reinermann, S.; Asam, S.; Kuenzer, C. Remote sensing of grassland production and management: A review. *Remote Sens.* **2020**, *12*, 1949. [CrossRef]
34. Zhang, Z.; Flores, P.; Igathinathane, C.; Naik, D.L.; Kiran, R.; Ransom, J.K. Wheat lodging detection from UAS imagery using machine learning algorithms. *Remote Sens.* **2020**, *12*, 1838. [CrossRef]
35. Hartfiel, L.M.; Digman, M.F. The impact of tedding on alfalfa nutritive value in a silage production system. *Appl. Eng. Agric.* **2021**, *37*, 1115–1118. [CrossRef]
36. Lim, J.; Sato, M.; Oishi, K.; Yamamoto, T. Simple in-field evaluation of moisture content in curing forage using NDVI. *Grassl. Sci.* **2020**, *66*, 89–99. [CrossRef]
37. Benning, R.; Birrell, S.; Geiger, D. Development of a multi-freqfuency dielectric sensing system for real-time forage moisture measurement. In Proceedings of the 2004 ASAE Annual Meeting, Ottawa, ON, Canada, 1–4 August 2004. [CrossRef]
38. Yu, D.; Park, S.; Moon, A. Transforming crop drying operations through IoT and data-driven solutions. In *Proceedings of the 2024 ICTC, Jeju, Republic of Korea, 16–18 October 2024*; IEEE: New York, NY, USA, 2024; pp. 142–147. [CrossRef]
39. *GB/T 25423-2023*; Rectangular Bale Baler. Standardization Administration of China: Beijing, China; State Administration for Market Regulation: Beijing, China, 2023. Available online: https://openstd.samr.gov.cn/bzgk/std/newGbInfo?hcno=FF0A1AD0F97F6E8E47249731337EDE8D (accessed on 20 August 2026).
40. Yin, W.; Pu, H.; Hu, F.; Zhai, C. Grain volume flow measurement method for combine harvester based on structured light vision. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 101–107. (In Chinese) [CrossRef]
41. Jin, C.; Chen, J.; Liu, Z.; Qian, Z. Review of agricultural machinery cooperative operation technology development in field operation scenarios. *Trans. Chin. Soc. Agric. Eng.* **2025**, *41*, 1–13. (In Chinese) [CrossRef]
42. Qian, Z.; Jin, C.; Liu, Z.; Wang, Y. Application status and trends of intelligent control technology in unmanned farms. *J. Intell. Agric. Equip.* **2023**, *4*, 1–13. (In Chinese) [CrossRef]
43. Wang, Y.J.; Huang, G.Q. Harvester scheduling joint with operator assignment. *Comput. Electron. Agric.* **2022**, *202*, 107354. [CrossRef]

44. Gómez, Y.; Stygar, A.; Boumans, I.; Norton, T. A systematic review on validated precision livestock farming technologies for pig production and its potential to assess animal welfare. *Front. Vet. Sci.* **2021**, *8*, 660565. [CrossRef]
45. Xu, Y.; Xie, Q.; Liu, H.; Wang, J. Research progress on monitoring methods during precision poultry breeding processes. *J. Domest. Anim. Ecol.* **2019**, *40*, 80–85. (In Chinese) [CrossRef]
46. Zhang, R.; Cao, S.; Kong, F.; Sun, W. Lightweight cattle face identity recognition method based on improved DenseNet121. *Trans. Chin. Soc. Agric. Eng.* **2026**, *42*, 212–220. (In Chinese) [CrossRef]
47. Lv, H.Y. Research on Individual Identification of Beef Cattle Based on Deep Learning Algorithms. Master's Thesis, Jiangxi Normal University, Nanchang, China, 2025.
48. Mora, M.; Pilés, M.; David, I.; Fabrega, E. Integrating computer vision algorithms and RFID system for identification and tracking of group-housed animals: An example with pigs. *Anim. Sci. J.* **2024**, *102*, skae174. [CrossRef]
49. Zhang, J.; Wang, X.; Meng, H.; Liu, Z. Semantically guided 3D reconstruction and body weight estimation method for dairy cows. *Agriculture* **2026**, *16*, 182. [CrossRef]
50. Kongsro, J. Estimation of pig weight using a Microsoft Kinect prototype imaging system. *Comput. Electron. Agric.* **2014**, *109*, 32–35. [CrossRef]
51. Condotta, I.; Brown-Brandl, T.; Silva-Miranda, K.; Stinn, J. Evaluation of a depth sensor for mass estimation of growing and finishing pigs. *Biosyst. Eng.* **2018**, *173*, 11–18. [CrossRef]
52. Ruchay, A.; Kober, V.; Dorofeev, K.; Marion, D. Accurate body measurement of live cattle using three depth cameras and non-rigid 3-D shape recovery. *Comput. Electron. Agric.* **2020**, *179*, 105821. [CrossRef]
53. Dohmen, R.; Catal, C.; Liu, Q. Computer vision-based weight estimation of livestock: A systematic literature review. *N. Z. J. Agric. Res.* **2022**, *65*, 227–247. [CrossRef]
54. Pezzuolo, A.; Guarino, M.; Sartori, L.; González, L. On-barn pig weight estimation based on body measurements by a Kinect v1 depth camera. *Comput. Electron. Agric.* **2018**, *148*, 29–36. [CrossRef]
55. Jiang, W.; Li, G.; Xu, J.; Chen, Y. Precision feeding systems in animal husbandry: Guiding rabbit farming from concept to implementation. *Agriculture* **2025**, *15*, 2215. [CrossRef]
56. Giannico, F.; Carbonara, C.; Jambrenghi, A.; Giammarco, M. Sensor-based precision feeding systems in animal production: Technologies and applications. *Animals* **2026**, *16*, 1333. [CrossRef]
57. Long, C.; Tan, H.; Zhu, M.; Li, W. Development of mobile intelligent monitoring platform for livestock housing. *Trans. Chin. Soc. Agric. Eng.* **2021**, *37*, 68–75. (In Chinese) [CrossRef]
58. Tuan, S.; Rustia, D.; Hsu, J.; Lin, T. Frequency modulated continuous wave radar-based system for monitoring dairy cow respiration rate. *Comput. Electron. Agric.* **2022**, *196*, 106913. [CrossRef]
59. Pastell, M.; Aisla, A.; Hautala, M.; Ahokas, J. A system for contact-free measurement of respiration rate of dairy cows. In Proceedings of the 3rd European Conference on Precision Livestock Farming, Skiathos, Greece, 20–22 September 2007; pp. 105–109.
60. Tedeschi, L.O.; Greenwood, P.L.; Halachmi, I. Advancements in sensor technology and decision support intelligent tools to assist smart livestock farming: A review. *J. Anim. Sci.* **2021**, *99*, skab231. [CrossRef]
61. Tu, S.; Liu, X.; Liang, Y.; Wang, M. Group-housed pig behavior recognition and tracking method based on improved DeepSORT. *Trans. Chin. Soc. Agric. Mach.* **2022**, *53*, 225–234. Available online: https://kns.cnki.net/kcms2/article/abstract?v=hH4QDuxDhLQ1MInv_jW46P5_awJCoufz4opAq0ZZijPvdH-82CAzqsF3r3lTgnY_egErnUCBTrZifPHQA5oQWGCoxbvBm5HvDgtDFU0dLxsMOR26XklqlPh6w5jI6jk5z-dlEg9Yt78AQM5LjsIrFcjzdCOgOEYoAPIIkp5MH2b7QHW774j8zg==&uniplatform=NZKPT&language=CHS (accessed on 23 August 2026). (In Chinese)
62. Mao, A.; Huang, E.; Wang, X.; Zhang, Y. Deep learning-based animal activity recognition with wearable sensors: Overview, challenges, and future directions. *Comput. Electron. Agric.* **2023**, *211*, 108043. [CrossRef]
63. Shebiah, R.; Arivazhagan, S.; Sree, K.; Raj, V. Cattle behavior recognition system using machine learning and Internet of Things. *Agric. Eng. Int. CIGR J.* **2024**, *26*, 251–260.
64. Essien, D.; Inyang, S.; Umoren, I. Evaluating machine learning classifiers and explainability for monitoring cow behaviour with wearable nose rings. *Prev. Vet. Med.* **2025**, *244*, 106630. [CrossRef]
65. Yue, Y.; Yu, L.; Hu, Y.; Zhang, Q. Class-specific feature selection for enhanced cattle behavior recognition using wearable-based system. *Smart Agric. Technol.* **2025**, *12*, 101548. [CrossRef]
66. Ni, G.; Jia, Y.; Shi, Z.; Li, X. A full end-to-end analytical framework for livestock behavior modeling and health assessment using wearable electronic recording system and machine learning. *Smart Agric. Technol.* **2026**, *13*, 101686. [CrossRef]
67. Benaissa, S.; Tuyttens, F.; Plets, D.; Stevens, M. Improved cattle behaviour monitoring by combining Ultra-Wideband location and accelerometer data. *Animal* **2023**, *17*, 100730. [CrossRef]
68. Rohan, A.; Rafaq, M.; Hasan, M.; Kim, K. Application of deep learning for livestock behaviour recognition: A systematic literature review. *Comput. Electron. Agric.* **2024**, *224*, 109115. [CrossRef]

69. Qin, X.; Liu, Z.; Zhao, C.; Wang, J. Application of machine vision technology in animal husbandry. *Agric. Eng.* **2021**, *11*, 27–33. (In Chinese)
70. Bai, Q.; Gao, R.; Zhao, C.; Ji, Z. Dairy cow multi-scale behavior recognition method based on improved YOLOv5s network. *Trans. Chin. Soc. Agric. Eng.* **2022**, *38*, 163–172. (In Chinese) [CrossRef]
71. Wang, Z.; Xu, X.; Hua, Z.; Li, Y. Lightweight dairy cow estrus behavior recognition fusing YOLOv5n and channel pruning algorithm. *Trans. Chin. Soc. Agric. Eng.* **2022**, *38*, 130–140. (In Chinese) [CrossRef]
72. Li, B.; Liu, D.; Shi, G.; Chen, J. Group-housed pig posture detection based on improved YOLOv4 model. *J. Zhejiang Agric. Sci.* **2023**, *35*, 1–10. (In Chinese) [CrossRef]
73. Wen, H.; Song, G.; Hao, K.; Li, Z. Application and research progress of intelligent robots in layer hen breeding. *China Poult.* **2019**, *41*, 53–57. (In Chinese) [CrossRef]
74. Thrun, S.; Burgard, W.; Fox, D. *Probabilistic Robotics*; MIT Press: Cambridge, MA, USA, 2005.
75. Song, H.; Duan, Y.; Li, R.; Zhai, C. Autonomous navigation system for intelligent push-feed robot in dairy barns based on LiDAR SLAM. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 293–301. (In Chinese) [CrossRef]
76. Lv, J.; Yao, B.; Guo, H.; Zhang, L. MOLO-SLAM: A semantic SLAM for accurate removal of dynamic objects in agricultural environments. *Agriculture* **2024**, *14*, 819. [CrossRef]
77. Tan, H.; Zhao, X.; Zhai, C.; Wang, L. Design and experiments with a SLAM system for low-density canopy environments in greenhouses based on an improved Cartographer framework. *Front. Plant Sci.* **2024**, *15*, 1276799. [CrossRef]
78. Sun, G.; Huang, Y.; Wang, X.; Li, H. Greenhouse autonomous walking system based on LIO-SAM mapping and LiDAR-vision fusion localization. *Trans. Chin. Soc. Agric. Eng.* **2024**, *40*, 227–238. (In Chinese) [CrossRef]
79. Mao, Y.; Yu, X.; Huang, K.; Zhang, Y.-J.A.; Zhang, J. Green Edge AI: A Contemporary Survey. *Proc. IEEE* **2024**, *112*, 1912–1943. [CrossRef]
80. Tangorra, F.; Buoio, E.; Calcante, A.; Lombini, G. Internet of Things (IoT): Sensors application in dairy cattle farming. *Animals* **2024**, *14*, 2687. [CrossRef]
81. Alonso, R.; Sition-Candancedo, L.; Garcia, O.; Prieto, M. An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario. *Ad Hoc Netw.* **2020**, *98*, 102047. [CrossRef]
82. Liu, C.; Lin, H.; Li, Y.; Zhang, Q. Research status and development trend analysis of intelligent control technology for agricultural equipment. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 1–18. (In Chinese) [CrossRef]
83. Verdouw, C.; Tekinerdogan, B.; Beulens, A.; Wolfert, S. Digital twins in smart farming. *Agric. Syst.* **2021**, *189*, 103046. [CrossRef]
84. Nasirahmadi, A.; Hensel, O. Toward the next generation of digitalization in agriculture based on digital twin paradigm. *Sensors* **2022**, *22*, 498. [CrossRef]
85. *GB/T 41187-2021*; Application Service for Agricultural Internet of Things. Standardization Administration of China: Beijing, China; State Administration for Market Regulation: Beijing, China, 2021. Available online: https://std.samr.gov.cn/gb/search/gbDetailed?id=D4BEFFF4EA62B241E05397BE0A0AF581 (accessed on 20 August 2026).
86. Sánchez, A.; García, J.; Pérez, M. Performance evaluation of wireless sensor networks in harsh agricultural environments. *Sensors* **2018**, *18*, 2835. [CrossRef]
87. Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. *Comput. Electron. Agric.* **2018**, *147*, 70–90. [CrossRef]
88. Gaitán-Jurado, D.; González-González, E.; Morales-Tortolero, A. Smart Solutions for Small Ruminants: The Role of Artificial Intelligence and Precision Livestock Farming in Smallholder Goat Husbandry. *AgriEngineering* **2024**, *8*, 103. [CrossRef]
89. China (Wuxi) IoT Research Institute. 2024 China Intelligent Sensor Industry Development Report. Available online: https://www.eet-china.com/mp/a369721.html (accessed on 30 June 2026).
90. Jaguemont, J.; Boulon, L.; Dubé, Y. A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures. *Appl. Energy* **2016**, *164*, 99–114. [CrossRef]
91. Zhang, Y.; Li, X.; Wang, H.; Chen, J. Ternary Dimension-Synergistic Conductive Architecture Enabling High-Rate, Low-Temperature and Extended-Cycling Nickel-Rich NCA Lithium-Ion Batteries. *Materials* **2026**, *19*, 1956. [CrossRef]
92. Tatar, E.; Mukherjee, T.; Fedder, G.K. Stress effects and compensation of bias drift in a MEMS vibratory-rate gyroscope. *J. Microelectromech. Syst.* **2017**, *26*, 569–579. [CrossRef]
93. Ruan, Y.; Chen, L.; Wu, H.; Zhao, M. Experimental study on temperature compensation for dual-axis MEMS accelerometers using adaptive mode decomposition and hybrid convolutional-recurrent temporal network modeling. *Micromachines* **2025**, *16*, 1284. [CrossRef]
94. Lee, W.W.; Nguyen, L.T.; Selvaduray, G.S. Solder joint fatigue models: Review and applicability to chip scale packages. *Microelectron. Reliab.* **2000**, *40*, 231–244. [CrossRef]
95. Chen, H.; Mueller, M.; Mattila, T.T.; Li, J.; Liu, X.; Wolter, K.J.; Paulasto-Kröckel, M. Localized recrystallization and cracking of lead-free solder interconnections under thermal cycling. *J. Mater. Res.* **2011**, *26*, 2103–2112. [CrossRef]
96. National Bureau of Statistics of China. *China Statistical Yearbook 2024*; China Statistics Press: Beijing, China, 2024. Available online: http://www.stats.gov.cn/sj/ndsj/2024/indexeh.htm (accessed on 30 June 2026).

97. Ministry of Agriculture and Rural Affairs of China. *National Animal Husbandry and Veterinary Work Bulletin 2024*; Ministry of Agriculture and Rural Affairs: Beijing, China, 2025. Available online: http://www.moa.gov.cn (accessed on 30 June 2026).
98. Cao, B.; Zhao, C.; Li, J.; Wang, X. Current status, challenges and prospects of smart agriculture technology development in China. *Trans. Chin. Soc. Agric. Eng.* **2025**, *41*, 1–10. (In Chinese) [CrossRef]
99. Kour, V.P.; Arora, S. Recent Developments of the Internet of Things in Agriculture: A Survey. *IEEE Access* **2020**, *8*, 129924–129957. [CrossRef]
100. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.-J. Big data in smart farming-A review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
101. Sapna; Gauttam, H.; Chauhan, V.; Pattanaik, K.K.; Trivedi, A.; Ghosh, H. A comprehensive review of Edge Computing empowered smart agriculture: Trends, Opportunities and Future directions. *Comput. Electron. Agric.* **2025**, *226*, 111252. [CrossRef]
102. Purcell, W.; Neubauer, T.; Mallinger, K. Digital Twins in agriculture: Challenges and opportunities for environmental sustainability. *Curr. Opin. Environ. Sustain.* **2023**, *61*, 101252. [CrossRef]

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