Research Advances in utilization of Feed Surplus in Pastures: From Intelligent Detection to Automatic Control

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Abstract. Intelligent detection and control methods for feed surplus in livestock farms are summarized and evaluated in this paper. Increasing scale and intensification render traditional feeding management inadequate for modern efficiency, welfare, and sustainability requirements. Intelligent and precise feeding management has become a key direction for industry transformation and upgrading. Traditional manual inspection decisions are plagued by high labour intensity, poor timeliness, and low precision. They not only increase production costs but also trigger animal health problems and environmental pollution. These issues hinder optimal feed resource allocation. In this research, the intelligent detection and control methods for feed surplus in livestock farms were summarized and evaluated. The applications of sensor fusion, machine vision, and intelligent inspection robots in feed surplus detection, and the principles, advantages, limitations of different detection technologies were analyzed. The types, structural designs, and performance characteristics of automatic feeding actuators were discussed. The current state of farm decision-making systems and preliminary IoT system construction were briefly summarized, with emphasis on various models and methods applied in farm systems. Current limitations were generalized and future research directions including multimodal fusion, edge intelligence, and lightweight models were proposed.

1. Introduction

Animal husbandry is a vital component of national economy. Traditional feeding in livestock farms relies on manual operations at fixed intervals, lacking real-time monitoring of feed surplus[1]. Breeding cots and animal production performance are significantly affected by feed management. With advances in sensor and automation technologies, the limitations of manual feeding, including low efficiency and precision have become increasingly apparent, impacting livestock growth. Comparative studies have demonstrated the benefits of automated systems. For example, J. Pang[2] implemented an intelligent feeding system in cow dairy farm, showing significant improvements in efficiency and cost-effectiveness over traditional TMR feeding equipment. Therefore, enhancing the intelligence of feed surplus detection and control is crucial for improving livestock growth and farm profitability.

Since the 21st century, advances in IoT and robotics have driven intelligent upgrades in feeding systems, with vision and machine learning technologies increasingly applied in automated feeding[3]. Researchers have utilized camera images and object detection algorithms to estimate residual feed volume or height[4]. Novel sensors such as laser rangefinders, 3D depth cameras, and pressure sensor arrays[5] have significantly improved detection accuracy and stability. However, current systems face challenges including low integration levels, communication protocol barriers, and high deployment costs for large-scale sensor networks. On the software side, Artificial Intelligence (AI) algorithms enable learning of feeding patterns and adaptive adjustments, while farm management systems integrate feeding, environmental control, and health monitoring modules[6] into comprehensive smart farm solutions[7]. Nevertheless, AI adaptation to diverse farm environments remains a significant challenge.

To address these challenges, we reviewed the research progress and applications in feed surplus detection and control for pastures. The core technical architecture of feed surplus detection and control is illustrated in Fig.1, briefly illustrating the methods for checking feed surplus, including machine vision applications, integrated sensors, inspection robots, automatic feeding technology, etc. It points out that the future direction of detection will develop towards more advanced sensing and cloud technology. The literature retrieved in this study mainly covers international authoritative academic journals such as Journal of Dairy Science and Computers and Electronics in Agriculture; domestic core journals such as Transactions of the Chinese Society for Agricultural Machinery and China Feed; renowned conference proceedings including IEEE and Springer; as well as Chinese and US patent databases. The publication years span from 2007 to 2025. Literature from the recent five years (2020–2025) is dominant, with particularly intensive citations of the latest research from 2023–2025.

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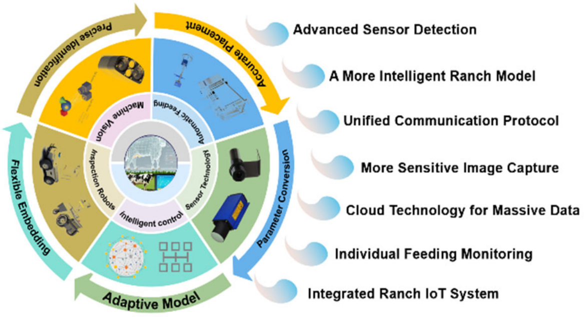

Fig 1. Intelligent Detection and Control of Feed Surplus in Pastures: It contains five important components feed surplus detection sensors, machine vision applications, Intelligent Inspection Robots and so on. The future direction of more intelligent development is pointed out. The goal is to build a universal pasture IoT system in the future.

Based on the summary in the above figure, a preliminary understanding of the classification and development of pasture feed surplus detection technologies has been obtained. The main contributions are as follows: Feed detection technologies are categorized into five types: feed surplus detection sensors, machine vision applications in feed image processing, intelligent inspection robots, automatic feeding technology, and Intelligent Control and IoT Architecture. A systematic analysis is conducted for each category, and the inherent relationships among different categories are explored; Extensive references are cited to analyze the development history of each technology. The work and innovations of multiple studies are summarized; Current problems in pasture feed management are summarized, including low precision and poor coordination. Possible future development trends are identified. The realization of future intelligent integrated livestock farms is envisioned; Recent technological developments in pasture feed management have been reviewed, limitations inherent in existing architectures have been critically analyzed, and prospects for future integrated and intelligent solutions have been envisioned.

2. Feed Surplus Detection and Control in Pastures

2.1 Feed Surplus Detection Technologies

As shown in Fig. 1, intelligent detection technology is a crucial part of feed testing in farms. Accurate perception of residual feed in troughs is the prerequisite for automatic feeding. Widely applied sensor technologies include mass sensors, ultrasonic ranging sensors, infrared laser sensors, and other novel sensing methods that directly reflect feed surplus. In recent years, object detection algorithms have become a popular research direction. Vision-based algorithms enable computers to identify and locate target feed areas in images or video frames for feed detection. Additionally, some researchers have developed compact intelligent inspection devices that integrate sensors, vision systems, and lightweight models to adapt to complex farm environments.

2.1.1 Feed Surplus Detection Sensors

Using sensors to directly or indirectly measure feed quantity is a common approach. For example, can be installed beneath feed troughs or hoppers to quality sensor determine residual feed by measuring weight changes. Zhang[8] proposed a feeding device. The device incorporates a pressure detection chamber below the trough. Pressure sensors measure the weight of the trough and feed. This allows accurate determination of residual feed quantity. Manual inspection by farm workers is eliminated. It intuitively reflects feed surplus through pressure changes; however, its sensitivity is questionable for detecting subtle feed variations. Moreover, retrofitting all feeding troughs in large-scale farms requires substantial labour, imposing significant limitations on this approach.

Infrared or laser ranging sensors are also used to measure the distance from the sensor to the feed surface, calculating feed layer thickness. When animals consume feed and the layer height decreases, the sensor detects an increased distance, indicating the need for refilling. These non-contact sensors are suitable for open troughs or silage pile height detection. J. Liu[9] designed an automatic metering system using infrared detection components at various height levels to measure residual feed volume in troughs, aligning measurement units between the trough feedback and feeding system while simplifying calculations. Ranging methods offer significantly improved sensitivity based on precise distance calculation, making them suitable for poultry with slow or irregular feeding behaviours. Laser sensors, also known as LiDAR, are non-destructive remote sensing technologies unaffected by lighting conditions[10]. Laser sensors are characterized by high measurement accuracy and strong anti-interference capabilities[11]. They have been widely adopted as important sensing devices in livestock farming. Basic ranging functions and critical robotic perception applications are both enabled. However, the high cost of LiDAR limits large-scale deployment, making it more suitable for mounting on lightweight inspection devices for ranging and mapping tasks.

Beyond conventional weight and ranging sensors, various sensor types are often integrated with technical components and communication protocols. H. L. Huergo[12] developed a remote monitoring system for livestock feeders that includes ranging sensors and short-range wireless transceivers to detect and identify livestock, monitor feeder volume, and communicate with external devices through multiple wireless methods. This multi-modal sensing approach with integrated communication offers greater operational flexibility. For granular or powdered feed, capacitive or resistive sensors can detect feed level height. R. Dalacort[13] developed a capacitive sensor system using an encoder coupled to a cylinder top to verify fertilizer depth and distribution. These sensors are cost-effective and easily installed on trough sidewalls, though feed composition and moisture may affect measurement accuracy, requiring calibration and algorithmic compensation. The authors tested eight formulations using static and dynamic metering mechanisms to address this issue. N. Pickens[14] designed a feed level sensor for poultry feeding systems using optical emitter-detector pairs within the drop tube to detect feed levels and trigger refill signals when feed reaches a predetermined "empty" level. These studies demonstrate diverse sensor types and applications for intelligent feeding detection.

Sensor technology offers advantages of real-time performance, continuous data acquisition, and direct integration with control systems for automatic feedback. However, individual sensors have limitations: weight sensors in large troughs may be affected by mechanical vibrations and animal biting, while ultrasonic ranging accuracy decreases in dusty environments. Therefore, multi-sensor information fusion is commonly adopted in practice to improve detection reliability. For example, combining weight and height sensors, or supplementing with temperature and humidity sensors to monitor feed quality, enables more comprehensive monitoring of feeder status.

2.1.2 Machine Vision Applications in Feed Image Processing

In the technological evolution of intelligent feeding systems for pastures, machine vision has advanced from traditional image processing relying on hand-crafted features to a new era of perception driven by deep learning. This transformation is fundamentally characterized by the rise and widespread application of single-stage object detection models. These models feature an end-to-end architecture. They achieve an excellent balance between speed and accuracy. They have become an indispensable technological foundation for real-time, online monitoring. The evolution of selected object detection algorithms was illustrated in Fig.2, including one-stage detection methods etc. This highlighted that machine vision applications in feed surplus detection represent a long-term and evolving process.

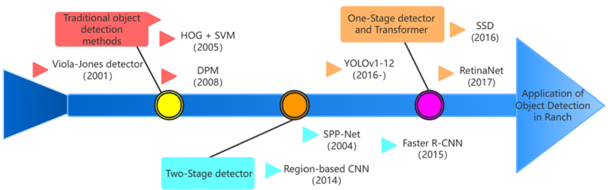

Fig 2. Application and Development of Object Detection Algorithms in Ranch Environments: Traditional object detection methods, two-stage detection methods, single-stage detection methods, and Transformer architectures are included. The chronological information of the algorithms is also presented in the figure.

Single-stage models represented by the YOLO[15] series reconstruct detection tasks as unified regression problems, directly predicting object categories and locations on images. By eliminating the time-consuming region proposal step required in traditional two-stage models like Faster R-CNN[16], significantly higher is the processing efficiency achieved. This enables seamless integration with video streams from feeding station cameras for real-time livestock identification and counting, intelligent access control at feeding station entrances, and precise monitoring of feeding duration and frequency. Continuous model iterations, beginning with YOLOv5's widespread application in detection, have demonstrated strong adaptability and considerable accuracy across various feeding environments, including aquaculture and cattle[17] and sheep feeding. From YOLOv5's engineering-friendly design to YOLOv8's added instance segmentation capabilities and the development of the YOLOv12 series, applications have expanded from bounding boxes to contour delineation, providing pixel-level precision for non-contact automated body condition scoring (BCS) and weight estimation. Meanwhile, specialized segmentation models such as U-Net and Mask R-CNN complement these applications in scenarios requiring extreme contour precision.

Image-based feed surplus detection technology utilizes machine vision and image processing to identify and estimate residual feed in troughs. It offers non-invasive, wide-coverage advantages, enabling real-time monitoring without disturbing animals, with advanced 3D RGB cameras providing hardware support for image acquisition[18]. M. Saar[19] developed a real-time machine vision system using RGB-D cameras to capture images of two feed types (lactating cow feed and heifer feed) at different weights, configurations, and lighting conditions, then employed two transfer learning models based on convolutional neural networks (CNN) to predict individual cow feed intake. R. Bezen[20] designed a computer vision system based on deep CNN and low-cost RGB-D cameras, achieving 93.65% cow identification accuracy with mean absolute error (MAE) and mean squared error of 0.127 kg and 0.034 kg for per-meal feed consumption, respectively. Z. Liu[21] proposed a feed volume detection method based on binocular stereo vision, using wooden blocks of different sizes to represent feed, achieving an average volume error of 7.12% compared to actual volume. However, the practicality and cost-effectiveness of binocular stereo vision and large real-time machine vision systems in large-scale livestock barns are questioned. More economical monocular RGB cameras are often sufficient. Portable mobile inspection devices can be equipped with these cameras. Lightweight object detection and depth estimation models are integrated. Therefore, integrating sensor and machine vision technologies, intelligent inspection robots offer a more convenient and flexible solution that is increasingly adopted.

2.1.3 Feed inspection robots

Beyond fixed sensors and cameras, mobile robotics has been introduced to feed inspection to replace manual patrols. Feed inspection robots are typically equipped with multiple sensors, such as LiDAR, cameras, and ultrasonic sensors, enabling autonomous navigation in barns or pastures for patrol detection of feed troughs.[22] Navigation and localization are key technologies, commonly achieved through pre-laid tracks, magnetic strip guidance, or Simultaneous Localization and Mapping (SLAM) for autonomous navigation[23]. LiDAR and vision sensors help robots avoid obstacles, ensuring inspection safety[24]. Onboard cameras or 3D scanners capture three-dimensional images of feed troughs, calculating residual feed volume through algorithms for more accurate quantitative detection with improved robustness and stability[25].

Autonomous inspection and feeding robots have been deployed in large-scale farms. A company in Beijing developed an intelligent feeding robot that moves along tracks or autonomous paths, monitoring residual feed in real-time and transmitting data to a central control system to trigger feeding when needed[26]. This mobile approach allows one robot to service multiple troughs, suitable for farms with dispersed layouts. Y. Li[27] proposed an IoT-based pig feeding management system using inspection vehicles and feeders with pressure sensors for control and data collection. H. Zhang[28] designed an inspection robot with wireless charging stations and depth cameras, using I-beam tracks for patrol scanning, reducing bio-security risks from manual inventory.

Intelligent inspection robots enable 24-hour automated operation in hazardous or restricted environments with improved efficiency and coverage. Equipped with advanced sensors and image recognition, robots accurately detect equipment defects, ensuring objective data collection. Automated data acquisition supports predictive maintenance, enabling farms to shift from reactive repair to proactive systems, improving safety and reducing costs. Future research focuses on multi-modal data fusion, enhanced robustness against occlusion and complex lighting, and model lightweighting for edge devices.

2.2 Automatic Feeding Technology

Following inspection, automatic feeding technology ensures equipment adds appropriate feed to troughs based on detection results. The objective is to deliver the right amount of feed to the right location at the right time, achieving unmanned and precise feeding. Automatic feeding systems typically consist of feeding devices, conveying mechanisms, and control systems, operating in either centralized or distributed feeding modes. Under intelligent farm management and decision control, automatic feeding demonstrates significant effectiveness[29].

Centralized feeding suits large-scale farms with concentrated troughs, offering unified feed management and centralized control. Distributed feeding provides rapid response and flexible control, allowing independent adjustment of feed quantity for each trough, suitable for different pens requiring different feed formulations or strategies. Automatic feeding actuators typically include feed hoppers, drive devices, and metering devices. Feed hoppers store feed, drive devices provide conveying power, and metering devices ensure accurate feed quantity. Metering can be achieved by controlling motor runtime or rotations, or through closed-loop weight control using load cell feedback for improved accuracy. Some researchers have also applied machine learning methods to predict feeding speed[30].

Control systems typically consist of PLCs or microcontrollers with host computer software. PLCs handle real-time control such as receiving sensor signals and motor operation, while host computers run algorithms to adjust feeding strategies based on historical data and growth models. F. Meng[31] developed a PLC-based automatic cow feeding system using sensors and PLC S7-1500 for data integration and control. Sun Wei created an automatic feeding device with robotic arms, conveyors, and pressure sensors. W. Sun[32] designed a slot-wheel metering mechanism with PLC-controlled stepper motors, achieving feeding error within 5%. W. Zeng[33] validated through comparative experiments that automatic feeding improves calf physiological indicators. These studies demonstrate the increasing adoption of automatic feeding technology in farms for real-time feeding and optimized livestock management.

2.3 Intelligent Control and IoT Architecture

Early automatic feeding systems used simple threshold control: feeding starts when residual feed falls below a lower threshold and stops at an upper threshold. This method is simple but lacks demand prediction and individual animal consideration. Modern farms employ complex control algorithms and decision models as part of farm IoT, using reliable communication networks to connect sensors, controllers, and actuators for data transmission and remote monitoring[34]. These systems integrate image, sound, and motion sensor data with algorithms to monitor animal behaviour, health[35], and management practices, serving as the decision-making "brain" that determines feeding timing and quantity based on detection data and management strategies.

Modern farm IoT employs various decision models: Predicting feed consumption using historical data and growth models enables proactive adjustments. Fuzzy reasoning systems encode expert experience to determine feeding timing and quantity based on trough residue, animal numbers, and frequency. Machine learning identifies consumption patterns and optimal strategies from large datasets, predicting demand based on time, season, weather, and physiological status. These model-based approaches enable intelligent control and provide the foundation for IoT architecture. IoT application reduces costs while enabling cloud-based intelligent services. Himanshu Agrawal[36] proposed an IoT system using virtual agents to process data and regulate feed supply.

The fundamental components and associated functions of the intelligent feeding IoT architecture on the ranch are revealed in Table 1. Intelligent feeding IoT in farms comprises field, network, platform, and application layers. An integrated operation from feeding information to action is formed through unified communication protocols.

Feed surplus detection data from sensors and actuators is transmitted via wired or wireless connections to local gateways. Cloud or local servers run management software for data storage, analysis, and visualization, controlling feeding equipment or triggering alarms. IoT integration enables feeding systems to interconnect with other farm management systems, forming a smart farm ecosystem that improves operational efficiency and facilitates data-driven decision-making.

Table 1. Components of Intelligent Control and IoT Architecture

Layers	Functions
Field	Collects real-time data from sensors and devices in the farm
Network	Transmits the collected data reliably to the cloud platform
Platform	Processes, stores, and analyzes the data to create insights and models
Application	Provides user interfaces and tools for farm management and decision-making

3. Key Technical Challenges and Future Development Trends

Despite significant progress in automatic feed surplus inspection and feeding technology, practical implementation still faces numerous challenges and technical difficulties that require further research.

Table 2. Comprehensive Comparison of Pasture Feed Surplus Detection and Utilization Technologies

Technology	Accuracy	Real-time	Adaptability	Investment	Application
Sensor	Moderate	<1s	Temp/humidity sensitive	Low	Fixed-point housed feeding
Machine Vision	High	30-60 FPS	Lighting sensitive	Moderate	Housed/semi-housed
Robot	High	1-3h cycle	Terrain/weather limited	High	Large-scale farms
Auto-feeding	High	On-demand	Most environments	High	Intensive farming
lo'T	-	20-500ms	Network dependent	High	System integration

As shown in Table 2, each technology exhibits significant differences in performance indicators, with no single "optimal" solution. Sensor technology has obvious advantages in terms of cost and real-time performance, making it suitable for basic monitoring in small and medium-sized farms with limited budgets. Machine vision technology demonstrates outstanding performance in accuracy and information richness, but has high environmental requirements. Inspection robots can theoretically achieve large-scale dynamic monitoring, but have the lowest technological maturity and still face major obstacles in commercial application. Automatic feeding technology has a high degree of commercialization, but requires large initial investment with a long payback period. IoT architecture is a necessary foundation for system integration and intelligent decision-making, but has high complexity and strong dependence on technical support.

3.1 Key Technical Challenges

3.1.1 Detection Accuracy and Environmental Robustness

Feed surplus detection is susceptible to multiple interfering factors, including variations in feed type, fluctuations in lighting conditions, and disturbances from animal activities. Currently, detection accuracy using single-sensor systems is limited. Additionally, maintaining long-term operational stability in complex farm environments remains a significant challenge that has not been adequately addressed.

3.1.2 System Integration and Standardization

The current industry suffers from a lack of unified standards among manufacturers. Data formats and communication protocols are incompatible across different systems, resulting in high integration costs and lengthy deployment periods. Consequently, coordination among subsystems is difficult to achieve, hindering the development of comprehensive farm management solutions.

3.1.3 Cost and Environmental Adaptability

Equipment reliability is significantly compromised by harsh farm conditions, leading to high failure rates. Maintenance costs are estimated to account a lot of total operating expenses. Furthermore, large-scale adoption is constrained by substantial initial investment requirements and extended payback periods, which pose considerable economic barriers for farm operators.

3.2 Future Development Trends

3.2.1. Multi-modal Fusion Sensing

Specifically, Cremona et al.'s research on 3D camera applications showed differences as low as 2% compared to nominal values in 2023. Furthermore, Bloch et al. found that RGB-D camera systems combined with CNN models achieved mean absolute errors of 0.241 kg for individual feed intake estimation in 2020. Additionally, volume estimation error is anticipated to be reduced to be less. These multi-sensor fusion approaches are regarded as promising solutions for achieving more reliable and precise feed surplus monitoring in practical applications. They are regarded as promising solutions for achieving more robust and precise feed surplus monitoring in practical livestock farming applications.

3.2.2. Edge Intelligence and Lightweight Models

Response latency can be reduced to under 50 milliseconds by deploying lightweight models such as YOLOv5 on edge computing devices. According to Qiao et al.'s study on cattle body detection in 2023, the YOLOv5-ASFF approach achieved a precision of 96.2%, a recall of 92%, Similarly, YOLOv8, YOLOv12, and other novel detection models need to be more widely applied in real-world scenarios to enhance their stability and accuracy. This edge-based approach enables real-time processing while maintaining detection performance and energy efficiency.

3.2.3. Standardization and Interoperability

Unified protocols like OPC UA and MQTT enable plug-and-play compatibility, significantly reducing integration costs and deployment time. Reinforcement learning and digital twin simulation optimize feed utilization. AI-driven precision feeding can be achieved within several years.

4. Conclusion

Research progress in automatic feed surplus inspection and feeding technology is systematically reviewed. We analyzed key technologies, including detection methods, automatic feeding systems, intelligent control, and IoT architectures, along with their current applications. Despite existing technical bottlenecks in detection accuracy, system integration, and cost control, developments in multi-modal fusion sensing, edge intelligence, and standardized protocols provide directions for overcoming these challenges. Technology is maturing and costs are declining. Intelligent feeding systems will be adopted more widely. Crucial support for digital transformation of animal husbandry will be provided. Breeding efficiency and animal welfare will be improved.

Acknowledgments

This work was supported by the National Key R&D Program of China (2024YFD1300600), the National Natural Science Foundation of China (No. 32272931), the National Natural Science Foundation of China (No. 32472964), the Shaanxi Province Agricultural Key Core Technology Project (2025NYGG005), and the Central Government’s Guidance Fund for Local Science and Technology Development (2025ZY-QYCXYL-04). All of the mentioned support is gratefully acknowledged. The authors would like to thank all of the authors cited in this article and the anonymous referees for their helpful comments and suggestions. Special thanks are extended to Professor H. Song for his meticulous guidance. Without his assistance, the completion of this paper would not have been possible.

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