Intelligent Waterfowl Farming: Research Status and Development Trends (Postprint)

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Abstract

Waterfowl farming is undergoing rapid development toward scaling, standardization, and intelligentization. Research and application of intelligent breeding equipment and information technology constitute the key to fostering healthy and sustainable development in the waterfowl farming industry, holding significant importance for enhancing production efficiency, reducing labor dependency throughout the production process, aligning with green and environmentally sustainable development principles, and achieving high-quality transformational development. This article emphasizes the latest research advances in intelligent waterfowl housing, intelligent environmental regulation technology for waterfowl housing, as well as intelligent equipment for waterfowl feeding, watering, medication and disinfection, and automated manure treatment. Furthermore, it presents the current status of information acquisition technologies applicable to waterfowl, encompassing visual imaging systems, sound capture systems, and wearable sensors, together with recent progress in the application of intelligent management technologies. Finally, it delineates the challenges confronting intelligent farming in the waterfowl industry and proposes recommendations for the future development and refinement of intelligent waterfowl farming.

Full Text

Status Quo of Waterfowl Intelligent Farming Research Review and Development Trend Analysis

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Abstract

Waterfowl farming in China is rapidly developing toward large-scale, standardized, and intelligent operations. Research and application of intelligent farming equipment and information technology are critical for promoting the healthy and sustainable development of the waterfowl industry, improving production efficiency, reducing labor dependency, aligning with green development concepts, and achieving high-quality transformational development. This paper focuses on the latest research progress in intelligent waterfowl housing, environmental control systems, and automated equipment for feeding, drinking, medication, disinfection, and manure treatment. Additionally, it reviews current information collection technologies applicable to waterfowl, including visual imaging systems, sound capture systems, and wearable sensors, along with recent advances in intelligent management technologies. Finally, the paper identifies challenges facing intelligent waterfowl farming and proposes future development directions and improvements.

Keywords: smart breeding; waterfowl farming; intelligent equipment; information collection technology; intelligent management platform; vision imaging; wearable sensor

2. Intelligent Waterfowl Farming Equipment

Large-scale multi-tier cage farming has opened new pathways for modern intensive waterfowl production, providing reference for designing waterfowl farming systems suited to China' s national conditions. In intensive waterfowl farms, feeding and manure cleaning are the most labor-intensive operations, followed by drinking water provision, environmental control, and disinfection. Intelligent equipment and environmental control systems can effectively reduce labor dependency, improve work efficiency, decrease manure treatment difficulty, and minimize feeding waste. Through intelligent perception and monitoring of waterfowl status, these systems enable precise management of farming processes, thereby enhancing control efficiency, reducing costs, and promoting the development of intelligent and automated waterfowl farming.

Currently, major intelligent waterfowl farming equipment includes intelligent waterfowl sheds, intelligent environmental control systems, intelligent feeding devices, intelligent drinking systems, intelligent medication and disinfection equipment, and automatic manure treatment systems.

2.1 Intelligent Waterfowl Sheds

Intelligent waterfowl sheds are intelligent structures designed specifically for waterfowl behavior, featuring automated farming and management functions to achieve targets of minimal human assistance or even unmanned operation. [Figure 1: see original paper] shows a smart waterfowl house demonstration site renovated by the South China Key Laboratory of Tropical Smart Agriculture Technology, Ministry of Agriculture and Rural Affairs. This shed uses rail-mounted inspection robots to monitor and obtain physiological and growth information of waterfowl, integrating artificial intelligence algorithms to provide technical reference for intelligent shed transformation. [Figure 2: see original paper] illustrates a German mobile poultry house that uses movable trailers to bring poultry farming closer to natural conditions, with automatic temperature and humidity regulation, automatic feeding, and automatic manure cleaning functions inside the trailer.

China' s waterfowl farming sheds have evolved through various stages: small open sheds, connected open sheds, low-frame sheds, dry-land sheds, net-bed sheds, fermentation bed sheds, fully enclosed sheds, and high-rise cage sheds, showing a trend of "increasing height" as shown in [Figure 3: see original paper]. High-rise cage sheds can better utilize vertical space, facilitate centralized manure treatment, and align with green development concepts, promoting transformation of traditional farming practices and representing future development trends.

However, most current sheds suffer from low mechanization development, resulting in predominantly manual operations and slow development of intelligent technologies. Intelligent equipment and farming technologies can further enhance the advantages of high-rise cage sheds, forming an economical, efficient, and environmentally friendly waterfowl farming model.

2.2 Intelligent Environmental Control in Sheds

A good waterfowl shed environment (evaluated through air temperature and humidity, carbon dioxide concentration, hydrogen sulfide concentration, and ammonia concentration) is crucial for waterfowl physiology, growth, and production. Intensive sheds easily accumulate harmful gases, suspended particles, and aerosol microorganisms, and without timely air regulation, can cause high-temperature heat stress and disease transmission. Therefore, optimized ventilation system design and temperature control systems are key for waterfowl sheds.

Currently, waterfowl shed monitoring remains largely manual or semi-mechanized, unable to effectively coordinate all environmental factors for comprehensive control. Pereira et al. used an IoT approach with multiple low-cost modular devices to collect environmental information, showing high correlation with calibrated equipment. Ying et al. designed a new net-bed duck house controlling ventilation through side curtains and equipped with wet curtains for temperature reduction, though these studies lacked further intelligent control methods and real-time capability. Guo et al. used artificial neural networks to replace manual control of goose house environment, reducing summer heat stress and mortality rates. Xu built an NH_3 concentration detection system for goose houses based on tunable diode laser absorption spectroscopy, finding that spectral detection had significantly lower linear and repeat errors than electrochemical detectors. Liu et al. developed a combined PCA-SVR-ARMA model for predicting temperature in lion-head goose breeding houses, providing decision support for precise temperature control.

While these studies attempted to apply intelligent models to replace manual regulation, they did not test equipment reliability and lifespan in complex, harsh environments. [Figure 4: see original paper] shows a reference layout for sensors and control equipment in cage-type sheds. By placing temperature and humidity sensors at different tiers and areas, comprehensive internal environmental information can be obtained. Intelligent environmental control for waterfowl sheds is achieved through IoT technology coordinating various sensors, control cabinets, servers, computers, web interfaces, and mobile apps. Based on analysis of multi-source sensor data, shed equipment is regulated through the intelligent control process shown in [Figure 5: see original paper].

2.3 Intelligent Feeding Equipment

Waterfowl intelligent feeding equipment enables large-scale, long-term feeding without human supervision, using computer vision, IoT, or artificial intelligence technologies to provide automated precision feeding according to waterfowl physiological and growth requirements. Typical intelligent feeding equipment includes automatic feed augers, centralized feed mixing towers, automatic feeders, and automatic feed carts ([Figure 6: see original paper]). Current automatic feeding primarily uses self-propelled feed carts, which distribute feed evenly but with low precision and intelligence.

Research and development of intelligent precision feeding equipment for waterfowl is advancing rapidly. Zhang et al. invented a waterfowl feeding device with precision feeding and feed recovery functions. Wen et al. and Yang invented waterfowl feeding devices with automatic feed delivery functions. Ren et al. designed an open-field automated duck feeding device for rice paddies enabling long-term fully automatic feeding without human attendance. Ni et al. designed a commercial automatic feeding system for laying ducks that effectively saves feed.

Research on intelligent feeding technology remains relatively weak. Developing characteristic feeding strategies for waterfowl of different growth statuses and species is the core objective of feeding intelligence. While this process is complex, inaccurate information collection models may lead to worse production efficiency. However, precision intelligent feeding technology has been proven to improve feed conversion efficiency and egg-laying capacity. Therefore, extremely high accuracy is required for waterfowl information collection. The inspection function attached to feed carts can collect accurate waterfowl data during feeding, precisely controlling feed intake to achieve "individualized feeding."

2.4 Intelligent Drinking Equipment

Waterfowl intelligent drinking equipment automatically provides water according to waterfowl needs without human supervision. Common drinkers are shown in [Figure 7: see original paper]. Current duck drinking equipment are mainly divided into closed and open systems. Open drinkers are easily contaminated, difficult to clean and maintain, labor-intensive, and cannot provide automatic water supply. Closed systems use nipple drinkers, which are clean, water-saving, and effectively prevent waterfowl from playing in water, which causes high indoor humidity and bacterial growth.

Current waterfowl drinking equipment has lower automation levels compared to layer and broiler chickens. Wang et al. invented an automatic waterfowl drinking device and validated it with Cherry Valley ducks, achieving 91.8% survival rate for breeding ducks aged 25-75 weeks under conditions matching duck behavior, realizing a certain degree of automation. Kong et al. invented an unmanned water supply control system for paddy field duck houses, enabling automatic control of field water supply systems. Such semi-automated, non-electric drinking devices are widely used in waterfowl farms. Similar to feeding devices, combining intelligent information collection technology can benefit waterfowl humidity regulation and improve welfare levels.

2.5 Intelligent Medication and Disinfection Equipment

Disinfection and epidemic prevention in waterfowl sheds play important roles in blocking external virus and bacterial invasion. [Figure 8: see original paper] shows three common intelligent disinfection devices. [FIGURE:8(a)] is a disinfection machine for personnel entry, using spray disinfection in the passage. [FIGURE:8(b)] shows a sustained-release disinfector that automatically releases required chemicals using dissolution methods for waterfowl diseases or wastewater treatment. However, medication through water treatment causes drug waste. Automatic medication devices can fully stir medicines automatically and adjust dosage according to disease severity to avoid waste.

A new research direction uses drug atomization to distribute diluted vaccine droplets in the shed. [FIGURE:8(c)] shows a spray disinfection robot; waterfowl receive immunity by inhaling medication through the respiratory tract, enabling thorough shed disinfection. This method offers advantages of low stress, fast immunity, and high efficiency.

2.6 Automatic Manure Treatment Equipment

Waterfowl automatic manure treatment combines automation control, intelligent technology, manure fermentation technology, and waterfowl farming, using conveyor belts to clean manure and replace traditional manual cleaning. In recent years, the trend of using conveyor belts for automated manure treatment has become increasingly apparent. Yu et al. developed an integrated cleaning and fermentation device for goose manure ([FIGURE:9(a)]), which uses conveyor belts to transport manure for centralized fermentation treatment. With the gradual rise of high-rise cage duck farming, placing conveyor belts under each cage level enables non-contact manure collection and centralized treatment. [FIGURE:9(b)] shows a three-dimensional cage duck manure conveyor belt that automatically activates when large amounts of manure accumulate, transporting it to fermentation pools, significantly improving air quality in duck houses.

3. Waterfowl Physiological Growth Information Collection and Intelligent Management

In large-scale farms, automatic waterfowl information collection is the foundation for intelligent analysis and decision-making, while perception devices determine the richness, effectiveness, and efficiency of waterfowl information, and perception models determine accuracy and intelligence levels. Currently, visual imaging systems, sound capture systems, and wearable sensors are mainstream methods for physiological and growth information perception.

3.1 Information Collection Technology

3.1.1 Visual Imaging System Visual imaging systems capture rich poultry image data. Different visual systems use different principles to collect images with different properties. Image features are then extracted through manual or automatic methods and combined with machine learning models for target tasks.

Color cameras enable poultry counting, behavior analysis, and movement tracking. Guo et al. used color cameras with artificial neural networks to monitor chicken distribution on the floor. Geffen et al. and Cao et al. used deep learning object detection networks for chicken counting. Pereira et al. used geometric features from color images with decision tree models to detect poultry behavior. Li et al. used Faster R-CNN to detect walking and preening behaviors. Zhuang et al. obtained pathological geometric features through computer vision and built support vector machine models to diagnose diseases. Wang et al. used hybrid support vector machine algorithms to track poultry numbers in pens. Khairunissa et al. used multi-object tracking and Single Shot MultiBox Detector (SSD) models to track poultry in color camera footage. While many algorithms exist for color camera-based poultry information collection, current research remains limited to specific scenarios with poor generalizability and limited computational speed, requiring further model parameter optimization and validation.

Thermal infrared cameras capture temperature matrix information from poultry for target detection, heat stress assessment, health determination, and dead/injured bird detection. Due to large temperature differences between poultry and the environment, this characteristic can be used for segmentation. Zaninelli et al. used temperature threshold methods for multi-target detection of poultry in thermal images. Many researchers have captured thermal images to obtain temperatures of key body parts (body surface, feet, head, face) to assess physiological status or disease conditions. Pereira et al. analyzed thermal comfort indicators of poultry clustering behavior using thermal images, providing technical reference for heat stress detection. Liu et al. used infrared imaging to successfully observe disease characteristics in poultry. Xu et al. designed a method for detecting leg abnormalities in poultry using thermal images. Thermal cameras have low temperature calculation accuracy without blackbody references. Additionally, temperature information alone is limited for disease diagnosis and requires combination with other indicators.

Three-dimensional cameras effectively capture 3D images to obtain volume information, often used for weight estimation research. Mortensen et al. used 3D cameras to predict poultry weight using age, 2D and 3D geometric features. Liu et al. developed weight estimation methods measuring poultry dimensions in regions of interest. Unlike less hairy animals, poultry feathers, posture changes, and wing movements affect weight estimation results, which most current studies have not addressed, requiring further model development considering practical issues.

3.1.2 Sound Capture System Poultry sounds can indicate health status and disease diagnosis, typically captured using microphones. Rizwan et al. developed a machine learning model to distinguish healthy from sick poultry using monitored sounds. Banakar et al. and Huang et al. extracted frequency domain features and mel spectrograms from poultry sounds to diagnose avian influenza using machine learning models. Liu et al. used hidden Markov model-based sound recognition to identify coughing and snoring sounds. Qin et al. recognized poultry cough sounds using audio technology and machine learning. Carpentier et al. developed a sound-based poultry health monitoring tool for automated sneeze detection. Cuan et al. detected avian influenza using convolutional neural networks on poultry sounds. Du et al. developed a machine learning-based poultry vocalization detection algorithm to assess thermal stress conditions.

Waterfowl can adopt similar or identical algorithms with retrained models. Current poultry sound capture system research remains in experimental stages with single scenarios. In practical applications, shed noise affects sound collection quality. Identifying problematic sound sources among numerous poultry, obtaining clear noise-free sound information, and locating sound sources remain current challenges.

3.1.3 Wearable Sensors Wearable sensors are typically worn as backpacks or leg rings, usually featuring acceleration measurement, temperature measurement, and identification functions. This information can determine poultry health status, welfare status, and daily behavior.

Okada et al. designed a lightweight poultry backpack sensor to detect highly pathogenic avian influenza through body temperature and movement monitoring, though temperature has certain lag effects in detecting fatal influenza. Triaxial accelerometers effectively monitor daily behavior. Banerjee et al. used backpack accelerometers with neural networks to monitor daily behavior. Yang et al. used backpack accelerometers with machine learning to successfully monitor walking, resting, feeding, and drinking behaviors.

Poultry leg rings typically use Radio Frequency Identification (RFID) technology. Placing RFID readers in designated areas can monitor behavior patterns, commonly applied to observe laying patterns. Sun et al. monitored individual laying patterns of Magang geese using leg rings and RFID readers in nest boxes. Li et al. designed an automatic egg collection and marking system using RFID leg rings to calculate nest entry time for laying ducks, determining whether they laid eggs. Zaninelli et al. used injected RFID sensors for laying behavior monitoring.

Unlike non-contact methods that heavily depend on model accuracy, contact sensors can obtain more accurate data through proximity advantages. However, for large-scale poultry farms, manual sensor deployment is time-consuming and labor-intensive with high equipment costs. Therefore, wearable sensors are more suitable for individual monitoring in smaller-scale scenarios or for monitoring group statistical patterns in large-scale operations.

3.2 Intelligent Management Platform

Currently, China' s waterfowl precision farming level is generally extensive with low efficiency, mainly characterized by poor health status, high mortality rates, underutilized genetic production potential, low feed conversion efficiency, and inefficient information collection. IoT and big data can drive welfare-based precision farming for waterfowl. By building intelligent management platforms, comprehensive transmission and storage of waterfowl precision farming information can be achieved, enabling remote control of production management data and intelligent equipment.

South China Agricultural University has designed an intelligent waterfowl big data platform specifically for industrialized duck farming, including real-time monitoring of multi-dimensional information such as environment, growth, and feeding, and achieving remote control of production management data and intelligent equipment, with a system shared for enterprise production management and control ([Figure 10: see original paper]).

System development mainly includes five aspects: (1) Construction of waterfowl farming databases, building information foundation databases for different breeds, physiological stages, and farming modes according to proposed metadata and data source standards; (2) Construction of waterfowl precision farming big data platforms; (3) Construction of IoT platforms integrating waterfowl farming information perception devices and systems; (4) Construction of algorithm platforms integrating waterfowl farming big data mining algorithms with big data platforms; and (5) Application demonstrations.

These components integrate IoT and big data access platform standards, core intelligent perception technologies, foundation information databases, and big data platforms, providing technical, standard, and platform support for precise and efficient waterfowl farming, promoting precision farming and production capacity improvement.

4. Difficulties and Development Trends

4.1 Existing Difficulties

Intensive waterfowl farming is the foundation for intelligent waterfowl farming, with intelligent equipment and environmental control systems as core components. With national emphasis on environmental protection and the need for large-scale efficient production on increasingly limited suitable land, improving production efficiency per unit area is urgent. Therefore, China urgently needs a new waterfowl farming model that is green, environmentally friendly, efficient, and has high land utilization.

Although current waterfowl intelligent management systems have achieved preliminary intensification and automation through automatic environmental control, drinking, feeding, manure cleaning, and medication disinfection equipment, large-scale promotion remains difficult due to four main issues:

First, few research results on waterfowl intelligent equipment exist, and existing results have low intelligence integration levels. In the poultry field, research on waterfowl-specific intelligent systems and equipment lags far behind chickens, without good integration with current mainstream algorithms.

Second, high costs for initial construction, talent training, and industry transformation. Waterfowl farming environmental intelligent control system construction involves multi-disciplinary integration that cannot be migrated from traditional farming technologies, resulting in high talent training and transformation costs. Most farming enterprises lack relevant personnel and technical reserves, and existing staff face difficulties transitioning from traditional to intelligent equipment. Meanwhile, few market suppliers can provide mature products and services, creating certain risks and thresholds with uncertain results.

Third, lack of unified standards constraining smart farming technology specifications. Waterfowl intelligent equipment currently lacks detailed technical standards for design specifications, relying on broader standards, resulting in non-uniform performance specifications or devices not truly suitable for waterfowl.

Fourth, low reliability of perception devices. Waterfowl sheds are in long-term high humidity, high corrosion, feather, and dust conditions, which corrode devices and shorten lifespans while causing feather and dust accumulation that reduces sensor sensitivity, challenging long-term high-load operation of perception devices.

4.2 Development Trends

With the development of smart farming technology, waterfowl farming production can become intelligent and automated through artificial intelligence, big data mining, intelligent perception, and smart equipment. The popularization of 5G technology plays a key role in farming industry informatization construction, and waterfowl farming-related technologies and equipment will greatly develop.

Future recommendations for waterfowl intelligent equipment include several priority areas. First, increase research investment in waterfowl-specific intelligent equipment to develop farming equipment more suitable for waterfowl. Currently, intelligent equipment works well for other animals, especially pigs, chickens, and cattle, but waterfowl-specific research remains weak. Many waterfowl sheds still use chicken equipment, which reduces waterfowl production or even causes death due to significant differences in body size, behavior, and growth patterns. Research should deeply integrate IoT and deep learning technologies to further optimize and improve waterfowl information collection technology, which depends on proper network deployment, sensor reliability, and management platform efficiency.

Second, waterfowl environmental intelligent control systems and equipment need more "grounded" transformation. Developing waterfowl intelligent equipment for high-rise cage sheds represents future trends. To avoid overly radical industrial upgrading, development strategies should align with China' s current waterfowl farming status, transforming existing mainstream equipment while promoting future industrial reform. Equipment R&D should align with current mainstream production models while leveraging research institutions' innovation capabilities and large enterprises' production experience through industry-academia-research collaboration to establish new high-rise cage demonstration sites and jointly promote transformation and upgrading of waterfowl intelligent control systems and equipment.

Third, during equipment commercialization, cultivation of waterfowl compound talents should accompany development. Intelligent waterfowl farming combines informatization, automation, and animal husbandry. Universities, especially agricultural institutions, should strengthen compound talent cultivation to build talent teams adapted to future intelligent waterfowl farming industries.

Fourth, develop technical standards and specifications for waterfowl intelligent equipment. Unified standards and specifications are the basis for university research goals and enterprise production organization, ensuring waterfowl product quality and improving market competitiveness of intelligent equipment.

Finally, develop reliable perception devices for waterfowl sheds. IoT technology in waterfowl sheds highly depends on sensor reliability. Reliable sensors providing timely, accurate, and effective perception information are critical for building waterfowl environment and physiological growth warning models. Corrosion-resistant materials and unique mechanical structures should be emphasized to mitigate corrosion effects and feather/dust accumulation.

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