Advances in Research and Application of Deep Learning in Smart Livestock Farming: A Postprint

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Abstract

Accurately and efficiently monitoring animal information, timely analyzing their physiological and health status, and integrating intelligent technologies for automated feeding and farming management are of great significance for large-scale livestock farming. Due to its automatic feature extraction and powerful image representation capabilities, deep learning technology is particularly suitable for animal information monitoring in complex livestock farming environments. To further analyze the research and application of artificial intelligence in contemporary smart animal husbandry, this paper focuses on three livestock species—cattle, sheep, and pigs—and reviews the current state of deep learning technology in target detection and recognition, body condition evaluation and weight estimation, as well as behavior recognition and quantitative analysis. Among these, target detection and recognition facilitate the construction of individual electronic archives for animals, upon which body condition and weight information, behavioral data, and health status can be integrated, representing a key development trend in smart animal husbandry. Currently, smart livestock farming technology faces challenges including multi-view, multi-scale, multi-scenario, and few-shot learning applications, along with issues regarding the generalization of intelligent technologies. Addressing the practical feeding and management requirements of animal husbandry, this paper provides an outlook on the development of smart animal husbandry and proposes: leveraging semi-supervised or few-shot learning to enhance the generalization capability of deep learning models; promoting unified collaboration and harmonious development among humans, equipment, and farmed animals; and achieving deep integration of big data, deep learning technology, and livestock farming, with the aim of further advancing the intelligent development of animal husbandry.

Full Text

Advances in the Applications of Deep Learning Technology for Livestock Smart Farming

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Abstract: Accurate and efficient monitoring of animal information, timely analysis of animal physiological and health conditions, and automated feeding and management through intelligent technologies are crucial for large-scale livestock farming. Deep learning techniques, with their automatic feature extraction and powerful image representation capabilities, are better suited for monitoring animal information in complex livestock environments. To further analyze the research and application of artificial intelligence in modern smart animal farming, this paper reviews the current state of deep learning technology for target detection and recognition, body condition evaluation and weight estimation, and behavior recognition and quantitative analysis in cattle, sheep, and pigs. Target detection and recognition facilitates the construction of individual electronic animal archives, enabling correlation with body condition, weight, behavior, and health information—representing the future trend of smart animal farming. Current intelligent livestock farming technologies face challenges including multi-perspective, multi-scale, multi-scenario, and small-sample applications, as well as issues with generalization. Based on practical breeding and management needs, this paper proposes development directions for smart animal farming: improving deep learning model generalization through semi-supervised or few-shot learning; achieving unified collaboration and harmonious development among humans, equipment, and animals; and promoting deep integration of big data, deep learning, and livestock farming to further advance intelligent animal farming development.

Keywords: smart animal farming; precision livestock farming; individual identification; information perception; behavior recognition; deep learning

1 Introduction

In smart animal farming, contact sensors (temperature, acceleration) and non-contact computer vision sensors are used individually or in combination to acquire animal information, followed by machine learning algorithms for modeling to achieve livestock target detection, body condition evaluation, and behavior recognition [**?**]. Computer vision technology is widely applied in livestock monitoring due to its objective and non-invasive advantages [**?**]. Early computer vision methods extracted manually designed features (color, shape, texture) from images or videos combined with machine learning algorithms for recognition and detection. However, overall accuracy heavily depended on feature extraction methods, and complex scenes, animal occlusion, and lighting conditions affected feature extraction and recognition performance. In recent years, deep learning development has overcome difficulties in visual feature representation, improved image and video understanding, and accelerated technological progress in computer vision for animal farming [?].

Neural networks for extracting animal visual features include Convolutional Neural Networks (CNN) [?], Region-CNN (R-CNN) [?], and YOLO (You Only Look Once) series [?, ?]. Animal video information often contains temporal information requiring extraction of sequential data. Common deep learning models for temporal information include Recurrent Neural Networks (RNN) [?], Long Short-Term Memory (LSTM) [?], and derivative algorithms [?, ?]. Combining these approaches to obtain spatiotemporal features can improve animal target detection and behavior recognition accuracy. Deep learning methods have been applied to animal information monitoring as decision support tools.

Figure 1 [Figure 1: see original paper] illustrates deep learning applications in smart animal farming. First, sensors acquire raw data reflecting livestock welfare and health. Second, deep learning extracts features from raw data to build information perception models, generating statistical information (e.g., behavior recognition statistics, individual identification statistics). Finally, deep learning algorithms feed statistical information back to farm management, decision-making, and regulation (e.g., production metrics, environmental control, precision feeding, disease prevention).

Although deep learning performs better than traditional computer vision in complex scenes, building intelligent livestock farming systems requires further exploration combined with practical conditions. For modern breeding industry needs including physiological information acquisition, growth and development, reproduction, health diagnosis, and breed selection, this paper focuses on cattle, pigs, and sheep to review and analyze deep learning technology for animal target detection and recognition, body condition evaluation and weight estimation, and behavior recognition and quantitative analysis. We discuss current challenges and future directions for modern animal farming to provide references for intelligent and precision management.

2 Animal Target Detection and Recognition

Animal target detection and recognition has become integral to animal farming and essential for modern precision scientific animal husbandry. In smart animal farming, timely animal target detection enables individual identification and information acquisition to establish individual animal archives, providing information support for digital management and product traceability.

Current individual animal detection and recognition typically assigns unique identifiers through plastic ear tags or RFID devices, but these methods face issues with equipment damage, loss, and collision interference. Recently, computer vision-based target detection and recognition methods have been widely applied in livestock identification research due to their non-contact and practical advantages, typically using visual features (shape, texture, color) combined with intelligent algorithms for target detection and recognition [?, ?]. Common sample images for individual animal detection include muzzle [?, ?], face [?, ?], and torso [?] regions for identification based on regional features (Figure 2 [Figure 2: see original paper]).

2.1 Face Detection and Recognition

Non-contact animal detection and recognition based on deep learning can effectively reduce farm pressure and promote precision scientific farming. Recent researchers have achieved efficient contactless detection and recognition of pig, sheep, and cattle faces. Xue et al. [?] proposed a sheep face detection method based on Euclidean space metric (SheepFaceNet) using natural environment sheep face images for training to achieve non-contact sheep identification. To address issues with redundant information and poor pose/angle in sheep face images, they proposed SheepFaceRepair for face alignment before recognition. Li et al. [?] combined Mobilenetv2 with Vision Transformer to propose MobileViTFace for sheep face detection, enhancing fine-grained feature extraction and suppressing background interference through Transformer. Kumar et al. [?] developed a deep learning network for individual cattle identification using muzzle images, employing CNN and Deep Belief Nets (DBN) for texture feature extraction, with Stacked Denoising Auto Encoder (SDAE) for feature encoding, outperforming state-of-the-art methods.

2.2 Whole Body and Key Region Detection and Recognition

Further detection and recognition of whole animals and key regions facilitates deeper information mining, such as positional relationships between legs and torso that reflect health status. Deep learning applications in this area require further exploration. Li and Li [?] used a highly similar pig face matching dataset to train Deformable Convolution Networks (DCN), obtaining deformed pig face datasets for training a tweaked CNN (TCNN) for facial landmark detection with only 5.60% error rate. He et al. [?] introduced dense blocks and SPP modules into YOLOv3, proposing YOLOv3-DB-SPP for pig detection with 90.18% average precision—9.87% higher than YOLOv3. Wei et al. [?] used YOLO-detected sheep faces for individual identification, achieving ~64% accuracy with VGGFace; using frontal sheep faces as input improved accuracy.

Qiao et al. [?] proposed a deep learning model for beef cattle identification using image sequences, extracting visual features via CNN and training LSTM to capture spatiotemporal information, achieving 88% and 91% accuracy with 15 and 20 frame sequences respectively. He et al. [?] proposed an improved YOLOv3 for dairy cow identification, achieving 95.91% accuracy at 32 f/s. Hu et al. [?] segmented cows into head, torso, and leg regions, extracting deep features through three independent CNNs with feature fusion and SVM classification, achieving 98.36% accuracy. Jiang et al. [?] proposed FLYOLOv3 for key region detection (torso, legs, head) in complex scenes, performing well on both day and night datasets.

2.3 UAV Image Target Detection

Grazing farms with large activity ranges often use Unmanned Aerial Vehicles (UAV) for monitoring. While UAV hardware processing has improved, algorithm performance still affects real-time detection, which deep learning can address. Andrew et al. [?] used R-CNN and Kernel Correlation Filter (KCF) for Holstein cow detection and tracking in UAV videos, then Inception V3-LSTM for individual identification with 98.1% accuracy. Shao et al. [?] and Barbedo et al. [?] achieved cattle detection and counting in UAV images using CNN. These studies demonstrate deep learning feasibility for UAV image detection. Applying deep learning to other hardware (robots, ground vehicles) represents a major future trend [?].

2.4 Summary

Despite progress, challenges remain, including lack of benchmark datasets and evaluation standards. Different datasets, preprocessing techniques, metrics, and models make comparisons difficult [?]. Detection results depend heavily on samples—accuracy is high for single, prominent targets but affected by detection methods, environmental conditions (lighting, occlusion), and image quality. Multi-angle datasets are needed for practical scenarios. Current face recognition datasets mostly contain frontal views, but heads appear at multiple angles in practice, requiring more complex datasets (multi-angle, day/night) and efficient, accurate, user-friendly detection systems.

3 Animal Body Condition Evaluation and Weight Estimation

Animal phenotypic information includes tail-head contour curvature, body length, and surface area—used for body condition scoring and weight estimation [?, ?]. Current research extracts morphological parameters through machine vision or deep learning models.

3.1 Body Condition Evaluation

Body Condition Score (BCS) is an important animal welfare indicator reflecting diet, fatness, productivity, and health [?]. For cattle (Figure 3 [Figure 3: see original paper]), BCS focuses on back, tail head, pin bones, hip bones, ribs, and chest. Traditional BCS uses tactile or visual methods by experienced farmers [?, ?], but these are subjective and environmentally sensitive, necessitating objective, accurate, and robust measurement methods.

Computer vision-based BCS typically uses rear or top views to obtain back region parameters [?]. Recent deep learning applications include: Kong and Chen [?] using Mask R-CNN with ResNet101-FPN and multi-task learning for pig weight and BCS prediction (5% and 3% accuracy improvement respectively); Çevik and Mustafa [?] using R-CNN for BCS region extraction (67.39% accuracy); Li et al. [?] using YOLOv2 to identify tail regions for BCS estimation (94.5% accuracy within 0.5 units); Huang et al. [?] using SSD for tail detection and BCS assessment (98.46% classification, 89.63% localization accuracy); Alvarez et al. [?] using Kinect v2 depth information with SqueezeNet and CNN (82% accuracy within 0.25 units, 97% within 0.5 units).

However, sample images often use single angles with only one animal per field of view. Practical environments require flexible imaging equipment. While 2D and 3D technologies show progress, 3D sensors are more expensive with complex data processing. Real-time BCS scoring in practical farming requires further exploration due to multi-pose, multi-scale, and occlusion challenges.

3.2 Weight Estimation

Animal weight is crucial for optimizing growth performance, increasing farmer income, and monitoring welfare, affecting milk production, growth, pregnancy, and fertility [?, ?]. Direct weighing using scales is accurate but time-consuming and stressful. Indirect methods use 2D/3D devices (RGB, thermal, LiDAR, TOF) to obtain phenotypic data and build weight models [?] (Figure 4 [Figure 4: see original paper]).

Deep learning applications include: Pezzuolo et al. [?] using depth cameras for pig measurements with 10% lower error than manual methods; Zhang et al. [?] comparing Xception, MobileNetV2, DenseNet201, and ResNet152V2 for pig weight estimation; Zhang et al. [?] using Intel Realsense D435 with Xception-based multi-output regression CNN; Ruchay et al. [?] using RGB-D images with bilateral filtering and CNN (9.1% mean absolute error); Gjergji et al. [?] showing CNN performed best for cattle weight prediction (23.19 kg error); Dohmen et al. [?] using Mask-RCNN with CNN (R^2=0.96, RMSE=20 kg).

Deep learning remains underexplored for weight estimation. Challenges include animal pose variation, shooting angles, and lighting. Practical systems must adapt to diverse lighting and motion conditions for reliable feature extraction. Integrating individual ID with body condition and weight monitoring in walking channels represents a promising direction.

3.3 Summary

Body condition evaluation primarily uses 2D/3D visual equipment with significant progress in scoring. However, 3D sensors are costlier and more complex than 2D. Uniform sample distribution across the complete 5-point BCS scale would improve system convergence and generalization. More objective, measurable BCS ground truth standards are needed to eliminate subjective scoring errors.

4 Animal Behavior Recognition

Animal behavior reflects health and physiological status, providing important management basis [?]. Monitoring methods include contact and non-contact approaches. Contact methods attach sensors to animals [?]; non-contact methods use image/video analysis [?]. Deep learning applies to both.

4.1 Contact-Based Animal Behavior Recognition

Contact sensors overcome manual monitoring limitations, reducing labor and improving intelligent management. Common sensors include accelerometers and acoustic devices (Figure 5 [Figure 5: see original paper]). Wang et al. [?] used neck-mounted microphones to compare DNN, CNN, and RNN for sheep feeding behavior, with RNN achieving 93.17% accuracy. Ying et al. [?] used collar-mounted accelerometers with wavelet denoising and GA-SVM for prenatal ewe behavior (97.88% accuracy). Zhang et al. [?] used three-axis accelerometers with CNN for sheep grazing behavior (93.8% average accuracy). Hao et al. [?] used Wi-Fi CSI with LSTM for dairy cow behavior (96.67% accuracy). Peng et al. [?] used inertial measurement units with LSTM-RNN for eight cattle behaviors (>80% accuracy). Hosseininoorbin et al. [?] used neck-mounted accelerometers with deep learning for beef cattle behavior (94.9% F1 for 2-class, 89.3% for 9-class).

Contact methods may cause animal stress and welfare issues. Sensor repositioning due to collar movement causes data loss/bias. Weak communication signals in farms challenge real-time data transmission. Current systems require extensive data accumulation to address farmer demands for health monitoring beyond just behavior.

4.2 Non-Contact Animal Behavior Recognition

Non-contact methods use computer vision systems to acquire images/videos, extracting biological visual and spatiotemporal features through deep learning for target detection and behavior classification.

4.2.1 Biological Visual Feature-Based Behavior Recognition These methods detect target regions and extract visual features for model training. Common models include YOLOv3 and YOLOv4. Kim et al. [?] used YOLOv3, YOLOv4, and improved YOLOv3 for pig feeding/drinking behavior (>90% accuracy), though group crowding remains challenging. Jiang et al. [?] used YOLOv4 for goat detection with position and centroid movement for behavior classification. Wang and He [?] improved YOLOv3 for dairy cow estrus detection (99.15% accuracy). Wu et al. [?] used YOLOv3 with relative step size features and LSTM for lameness detection (98.57% accuracy). Ayadi et al. [?] used CNN for cattle rumination detection (95% accuracy).

These studies focus on image features without temporal information, and are vulnerable to environmental interference (lighting, background). Applicability across different farm scenarios requires further exploration.

4.2.2 Spatiotemporal Feature-Based Behavior Recognition Animal behavior is a continuous process containing both spatial and temporal information. Extracting temporal features is crucial [?]. Chen et al. [?] combined Xception and LSTM for pig drinking behavior detection. Guo et al. [?] and Qiao et al. [?] built BiGRU-attention and C3D-ConvLSTM models for dairy cow behavior recognition, achieving ~82% and 95.5% accuracy respectively across different growth stages. Jiang et al. [?] used single-stream optical flow convolution networks for lameness detection (98.24% accuracy). Wu et al. [?] used CNN-LSTM for five cattle behaviors, outperforming visual-only models.

Most studies combine CNN with LSTM for spatiotemporal features, but similar behaviors (e.g., drinking vs. playing) remain challenging. Further research is needed.

4.4 Summary

Current behavior research lacks quantitative analysis (feeding frequency, movement duration, rumination time). Analyzing semantic relationships between animals and environment through scene graphs, and quantifying different behaviors in spatiotemporal domains to construct behavior atlases can provide scientific basis for abnormal behavior detection and precision management. Quantifying behavior duration and amplitude improves management efficiency. Most studies qualitatively analyze effects of feed, light, temperature, and bedding on behavior [?] through manual observation [?, ?]. Computer vision technology is increasingly applied to assess animal-environment correlations [?], but challenges remain in recognizing environment-interactive behaviors (e.g., misidentifying static heads or shadows as feeding). Deep learning applications in this area remain limited and require further exploration.

5 Challenges and Prospects

Large-scale, standardized, intelligent precision health farming is the trend. Although China’ s large-scale farming has improved rapidly, most dairy farms remain at initial intelligent management stages with low informatization and automation. Deep learning enhances remote information perception, growth monitoring, and health surveillance for precision management. However, challenges remain:

1. **Model Generalization:** Deep learning requires large labeled datasets but faces limitations when generalizing to new datasets or animal types. Labeling livestock images/videos is time-consuming (e.g., BCS scoring, subtle behavior annotation). Combining semi-supervised or few-shot learning to improve generalization for real-time, all-weather monitoring

remains challenging. While image augmentation through style transfer can expand samples, differences from real environments persist. Few-shot research applications in livestock require further exploration.

2. **Human-Equipment-Animal Collaboration:** Intelligent equipment improves efficiency and reduces labor, but balancing animal welfare with operational convenience requires continuous theoretical and practical development to improve overall efficiency and management.
3. **Deep Integration of Big Data and Deep Learning:** With IoT and sensor development, data quantity and quality have improved. Establishing unified, efficient livestock industry data standards enhances security and maintainability. Applying intelligent technology to disease prevention, precision feeding, environmental control, and breed selection drives smart farming development. However, equipment layout, real-time data transmission, algorithm performance, and linking monitoring results with health information remain challenging.
4. **Interpretability and Security:** Deep learning' s "end-to-end" decision mode lacks interpretability—understanding what knowledge the model learns and how decisions are made. This weakness persists despite high accuracy. Security concerns arise from algorithm complexity, numerous parameters, and massive data requirements, creating vulnerabilities that could impact management and economics. Safety research becomes crucial as AI technology spreads.

In conclusion, deep learning is gradually applied to livestock identification and health monitoring, but real-time, multi-scenario applications require further model optimization. Practical challenges including different growth stages and breeds require continuous development. Combining actual breeding modes, spatial layouts, management approaches, and production expectations to develop intelligent monitoring systems will drive livestock industry development.

Conflict of Interest Statement: This study has no conflicts of interest among researchers or with publicly disclosed research outcomes.

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Note: Figure translations are in progress. See original paper for figures.