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Editorial

Application of Vision Technology and Artificial Intelligence in Smart Farming

Xiuguo Zou [1,2,*], Zheng Liu [2], Xiaochen Zhu [3], Wentian Zhang [4], Yan Qian [1] and Yuhua Li [1]

1 College of Artificial Intelligence, Nanjing Agricultural University, Nanjing 210031, China
2 Faculty of Applied Science, University of British Columbia, Kelowna, BC V1V 1V7, Canada
3 School of Applied Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China
4 Faculty of Engineering and Information Technology, University of Technology Sydney, Sydney, NSW 2007, Australia
* Correspondence: zouxiuguo@njau.edu.cn or xzou05@mail.ubc.ca; Tel.: +86-25-58606585

With the rapid advancement of technology, traditional farming is gradually transitioning into smart farming. Smart farming is an agricultural production system that harnesses modern technologies such as artificial intelligence (AI), big data, and automation technology, which assists farmers in effectively managing and optimizing the production process through data and image analysis. The ultimate goal of smart farming is to achieve precision agriculture and enhance efficiency and quality in agricultural production.

This Special Issue focuses on the application of visual technology and artificial intelligence in smart farming. Researchers from Asia and Europe have contributed a total of fourteen papers, including thirteen articles and one review, to this issue. The key information for each paper is shown in Table 1. These papers encompass a broad spectrum of technologies, such as image recognition algorithms, machine learning techniques, remote sensing technology, and 3D point cloud technology. The objective is to employ these technologies for monitoring the phenotypes of plants and animals, as well as their growth environments. By offering theoretical and technical support, personalized agricultural management solutions are made accessible to farmers.

Machine learning is a widely used modeling technique that leverages large quantities of data to acquire knowledge and make predictions. It can be applied to forecast trends in the growth environment of animals and plants. For example, Ren et al. [1] developed a prediction model for relative soil moisture (RHs 10 cm) in the 0–10 cm soil layer using the extreme gradient boosting (XGBoost) algorithm based on atmospheric and soil factors, which is capable of reasonably predicting the development process of drought events. Analyzing and predicting the growth environment of crops using data analysis methods can provide preventive measures for potential hazards. This method is equally effective for poultry farming.

Deep learning is a specialized machine learning field based on artificial neural networks. It involves learning and training through multi-layered neural networks to extract complex features and patterns from data, enabling more precise predictions. It is particularly suitable for handling complex, large-scale data and high-dimensional features and has wide applications in the field of computer vision. Applying deep learning models to analyze RGB images, remote sensing images, and 3D point cloud data in agriculture can enable more accurate monitoring of phenotypes of animals and plants, facilitating precision farming management. Jiao et al. [2] developed predictive models for the initial flowering period of Platycladus orientalis (Chinese thuja) using recurrent neural networks (RNN), long short-term memory networks (LSTM), and gated recurrent units (GRU). Shapely Additive Explanation (SHAP) was used to analyze the contribution rates of meteorological factors. The accuracy of all three models was significantly higher than that of a regression

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model based on the accumulated temperature. Among them, the GRU model performed the best, with an average accuracy exceeding 98%. Guo et al. [3] proposed an improved YOLOv5 object detection model, integrating the coordinate attention module and the deformable convolution module for accurately detecting mature Zanthoxylum on a mobile picking platform, addressing the issues of irregular shape and occlusion caused by branches and leaves. Li et al. [4] proposed a lightweight wheat growth stage detection model and a dynamic migration algorithm, which utilizes edge computing to migrate the detection model to the wireless network edge server for processing, improving efficiency significantly compared to the local implementation. By accurately monitoring the growth trends of animals and plants through deep learning and computer vision technologies, they can effectively improve production efficiency. In addition, this technology can also be applied to classification tasks to achieve personalized management of the same type of subjects. Zhang et al. [5] proposed a method for identifying individual dairy cattle in large-scale dairy farms. They used the DeepOtsu model to binarize the body pattern image for primary classification and the EfficientNet-B1 model for secondary classification, and the overall identification accuracy reached 98.5%. Cui et al. [6] proposed an improved CNN-LSTM model for classifying high-yield and low-yield cow udders that have undergone fine-grained segmentation using the SOLOv2 method, which could allocate them to different production groups.

Table 1. The key information for each paper.

Authors	Objects	Models	Contributions
Ren et al. [1]	Soil Moisture	Extreme Gradient Boosting	Establish prediction models of soil relative humidity
Jiao et al. [2]	Platycladus Orientalis	Gated Recurrent Unit	Predict the initial flowering period
Guo et al. [3]	Zanthoxylum	YOLOv5	Identify mature Zanthoxylum fruits
Li et al. [4]	Wheat	A Lightweight CNN	Identify wheat growth stages
Zhang et al. [5]	Cow	DeepOtsu EfficientNet	Identify individual cows
Cui et al. [6]	Cow	SOLOv2 CNN-LSTM	Divide cow production groups
Ding et al. [7]	Apple	RFCA ResNet	Identify apple leaf diseases
Hao et al. [8]	Hens	Faster R-CNN	Monitor the feeding behavior of hens
Lee et al. [9]	Honey Bee	BFMatcher	Monitor bee mites and diseases
Yu et al. [10]	Grain	FcsNet	Recognize grain pest species
He et al. [11]	Rice Seed	Multimodal Fusion	Classify rice varieties
Sun et al. [12]	Soybean	RandLA-Net BAAF-Net	Construct an annotated three-dimensional model dataset
Xu et al. [13]	Maize	Multi-view Registration Algorithm Iterative Nearest Point Algorithm	Realize early variety selection at the seedling stage
Karunathilake et al. [14]	Multi Objects	Multi Models	A review of the latest advances in precision agriculture

Furthermore, visual technology can detect diseases based on the phenotypic information of animals and plants, providing early warnings for farmers to reduce economic losses. Therefore, the accuracy of model recognition is particularly important for the practical application. Several authors in this issue have researched model improvement. Ding et al. [7] proposed a novel model called RFCA ResNet, which incorporates multi-scale feature extraction and a dual attention mechanism for classifying and recognizing apple leaf diseases. Additionally, the adverse effects of imbalanced datasets on classification accuracy were effectively minimized using the class balance technique in conjunction with focal loss. Hao et al. [8] proposed an improved Faster R-CNN network characterized by the fusion of a 101 layers-deep residual network (ResNet101) and Path Aggregation Network (PAN) for monitoring the feeding behavior of hens, and the ability of the model to extract features is greatly enhanced according to the visualization results of the feature map output by the convolutional layer at each stage of the network. Lee et al. [9] proposed an image-processing method based on a keypoint detection algorithm and image-matching algorithms for detecting small-sized honey mites attached to bees, which can result in economic losses. Additionally, they employed Contrast Limited Adaptive Histogram Equalization (CLAHE) based on the RGB color model to enhance image quality. Their method demonstrated effective performance when applied to the measured 300 mm data. Yu et al. [10] proposed a stored grain pest identification method based on a triple-attention module (FCS), namely, frequency domain attention (FAM), channel attention (CAM), and spatial attention (SAM) to solve pest-detection and segmentation tasks.

However, the improvement in the recognition accuracy of models relying solely on single-image information is limited, making it difficult to capture image features and abstract concepts in complex tasks, which leads to less accurate or complete processing results. Some models require a large amount of annotated data for training, and the lack of sufficient data can affect the effectiveness and generalization ability. When image processing techniques are combined with other technologies, including multidimensional images, data fusion, etc., it enables more precise monitoring of subjects in farming. He et al. [11] proposed a novel decision-making method based on a multimodal fusion detection model, and multiple models were used to predict the rice seed varieties according to 2D images and 3D point cloud datasets to calculate a comprehensive score vector. Finally, the predicted probabilities from 2D and 3D were jointly weighted to obtain the final predicted probability, which could combine the advantages of different data modalities and significantly improve the final prediction results. Sun et al. [12] used multi-view stereoscopic technology (MVS) to reconstruct the entire growth period (13 stages) of five different soybean varieties in three dimensions, constructed a 3D dataset named Soybean-MVS with the labels of the entire soybean growth period, and used RandLA-Net and BAAF-Net two point cloud semantic segmentation models to verify its usability, which can provide usable basic data support for the 3D crop model segmentation models. Xu et al. [13] proposed a reconstruction algorithm based on 3D information for the detection of maize phenotypic traits, utilizing a multi-view registration algorithm and iterative closest point (ICP) algorithm for the global 3D reconstruction of maize seedling populations, which contributes to precise and intelligent early management of maize.

The works received for this Special Issue demonstrate the feasibility of applying artificial intelligence and visual technologies in smart farming. Karunathilake et al. [14] provide a comprehensive overview of the recent innovations in smart farming technology, such as drones, sensors, and automation. The agricultural environment is practically diverse and challenging, with variations in soil conditions, climate patterns, and so on. To develop effective models for smart farming, it is essential to create algorithms that can generalize well across different environments. Moreover, the health and growth of plants and animals are influenced by a range of factors, so the integration of multimodal data and the fusion of multiple features hold great potential for improving the accuracy of predictions and identifications in smart farming applications. Despite the potential benefits of smart farming technology, there are challenges to promoting and popularizing its application. The technology must not only meet practical application requirements, but also address issues such as cost and farmer acceptance. On the one hand, hardware, software, and maintenance costs should be affordable for small and medium-sized farmers. On the other hand, the widespread implementation of smart farming technology requires a strong digital infrastructure and connectivity. In many rural areas, the lack of reliable internet and mobile networks can hinder the deployment of smart farming solutions, and this issue may be addressed well by cloud-edge coordinated computing, achieving more efficient computing and data processing. This Special Issue contains papers related to the above innovative research and will hopefully stimulate further research in these areas.

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