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Editorial

Novel Applications of Optical Sensors and Machine Learning in Agricultural Monitoring

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The rapid development of intelligence and automated technologies has provided new management opportunities for agricultural production. In particular, the progress of remote sensing equipment has allowed for vast improvements in the spatial, temporal, and spectral resolutions of optical sensors. Such sensors are key in current agricultural production management practices, with applications in areas that were previously explored using field observations, including the monitoring of plant health, growth conditions, and pest infestations.

The papers published in this Special Issue, "Novel Applications of Optical Sensors and Machine Learning in Agricultural Monitoring", present some of the most current and novel results of scholars' investigations on the applications of optical sensors and machine learning in the field of agriculture. Table 1 summarizes the 16 peer-reviewed articles included in this Special Issue. We found the guest editing for this exercise to be very inspiring, with contents including:

(1) The application of machine learning techniques to examine the key physiological development and production variables of crops.
(2) The use of datasets obtained from multiple sources and sensors to enhance crop mapping.
(3) Advanced target recognition algorithm techniques for weed and disease identification.

The optical sensors used in the presented research include a digital RGB camera, spectrometers, a 3D TOF sensor, a multispectral imaging sensor, and a satellite-based multispectral sensor. The machine learning methods include conventional machine learning techniques such as KNN, RF, SVM, and ANN, and deep learning techniques such as LSTM, VGG, YOLO, and SSD.

The contributions to this Special Issue are summarized in the following.

Wang et al. [1] employed LAI as the input to four machine learning models (RF, SVR, PLSR, and XGBOOST) and one deep learning model (LSTM) for winter wheat production estimates in Henan Province, China, during 2016. The results indicated that the LSTM performed better than the four traditional machine learning models, exhibiting the optimal R^2 and RMSE values. Kumar et al. [9] investigated the canopy cover of sugarcane and its relationship with dry matter and yield, and analyzed the relationship between (a) canopy temperature, chlorophyll fluorescence, SPAD index, and (b) yield. Luo et al. [13] fused vegetation indices determined using a UAV with brightness, greenness, and moisture indices estimated using tasseled cap transformation (TCT). The proposed approach was observed to enhance the accuracy of rice yield predictions and was able to avoid the saturation phenomenon.

Table 1. Summary of publications featured in this Special Issue.

Article	Agricultural Activities/Variables	Optical Sensors	Platforms	Machine Learning Methods
[1]	Winter wheat yield prediction	MODIS	Satellite	LSTM, RF, SVR, PLSR, and XGBoost
[2]	Land use/cover classification	Sentinel-2 MSI	Satellite	RF
[3]	Wheat fusarium head blight	Multispectral imaging sensor	UAV	KNN, SVM, XGBoost
[4]	Cropland spatial distribution	Landsat 8 OLI	Satellite	Blanket covering method
[5]	Soybean FVC, LCC, and maturity	SONY DSC-QX100	UAV	RF, PLSR, GPR, MSR
[6]	Apple leaf diseases	Canon Rebel T5i DSLR	Field	BTC-YOLOv5s, YOLOv5, SSD, R-CNN, Faster R-CNN, YOLOv4-tiny, and YOLOx, YOLOx-s
[7]	Crop classification	Sentinel-2	Satellite	1D-CNNs, LSTM, 2D-CNNs, 3D-CNNs, and ConvLSTM2D
[8]	Dairy herd fatness	3D TOF sensor	Field	BCS
[9]	Sugarcane dry matter and cane yield	Mobile phone camera	Field	Two-Way cluster
[10]	Peanut southern blight severity	ASD Field Spec3 VNIR-SWIR sensor	Field	SVM, DT, and KNN
[11]	Corn diseases	digital camera	Field	VGNet, VGG16
[12]	Soil moisture content	ASD Field Spec3 VNIR-SWIR sensor	Field	PCA, PCR, PLSR, and BP-ANN
[13]	Rice yield	Mini-MCA 1000	UAV	TCT
[14]	Weed detection in peanut fields	Fuji Finepixs4500	Field	YOLOv4-Tiny, YOLOv5s, Swin-Transformer, Faster-RCNN, YOLOv6-Tiny, and EM-YOLOv4-Tiny
[15]	Vegetation canopy reflectance angle normalization	GOCI	Satellite	SANM
[16]	Soybean maturity	SONY DSC-QX100	UAV	SVM, RF, InceptionResNetV2, MobileNetV2, Alexnet, ResNet50, and DS-SoybeanNet

Note: UAV, unmanned aerial vehicle; RF, random forest; TCT, tasseled cap transformation; SANM, synthetic angle normalization model; PCA, principal component analysis; LSTM, long short-term memory; SVR, support vector regression; PLSR, partial least squares regression; XGBoost, eXtreme gradient boosting; DT, decision tree; KNN, K-nearest neighbor; SVM, support vector machine; GPR, Gaussian process regression; MSR, stepwise multiple linear regression; YOLO, you only look once; SSD, single shot multi-box detector; CNN, convolutional neural network; R-CNN, regions-convolutional neural network; BCS, body condition scoring; PCA, principal component analysis; and BP-ANN, back propagation-artificial neural network.

In order to enhance the estimation accuracy of LULC models, Ibrahim [2] performed RF-based feature selection using data obtained from Sentinel-1, -2, and the Shuttle Radar Topographic Mission. The author revealed that integrating optical, radar, and elevation information is key to increasing the precision of LULC models for agriculturally dominated landscapes. Wang et al. [4] developed an information extraction method for the accurate determination of the spatial distribution of crops by integrating spatiotemporal image information using a fractal model. The authors demonstrated the ability of their approach to determine key cropland variables for the effective monitoring, conservation, and development of black soil. Li et al. [7] developed a 3D-CNN and ConvLSTM2D method for the classification of crops across time. Five deep learning models were tested, namely 1D-CNNs, LSTM, 2D-CNNs, 3D-CNNs, and ConvLSTM2D. 3D-CNN and ConvLSTM2D, which combine temporal, spectral, and spatial information, outperformed the other models in terms of crop classification using time series images.

Gao et al. [3] developed an approach based on UAV and multispectral imagery that integrated the spectral and textural features of images to examine wheat fusarium head blight (FHB) and estimate several Vis and Tis. The VIs, TIs, and combined VIs and TIs were adopted as the inputs to KNN, PSO-SVM, and XGBoost to develop wheat FHB monitoring models. The proposed approach was revealed to have potential for fast and nonintrusive observations of wheat FHB. Guo et al. [10] proposed the Peanut Southern Blight Severity method by combining hyperspectral data, continuous wavelet transform, and machine learning. The machine learning methods SVM, DT, and KNN were tested and compared. Fan et al. [11] developed a VGNet with the backbone set as VGG16, with the ability to improve the recognition of corn with poor health in fields. In particular, there was a 3.5% enhancement in the accuracy of the proposed VGNet compared to its predecessor VGG16.

Hu et al. [5] developed a soybean maturity recognition approach that combined UAV-based LCC and FVC maps with an anomaly detection method, exhibiting total monitoring accuracies greater than 98%. Zhang et al. [16] designed the novel CNN DS-SoybeanNet to enhance UAV-based soybean maturity observations, with the ability to extract and employ shallow and deep image features. The authors compared it with the widely used Alexnet, InceptionResNetV2, MobileNetV2, ResNet50, SVM, and RF, revealing the high accuracy of DS-SoybeanNet in soybean maturity classification.

Yurochka et al. [8] developed an approach for the automatic evaluation of dairy herd fatness using a 3D TOF sensor and the body condition score (BCS). The proposed approach was able to perform nonintrusive BCS evaluations of dairy herds throughout the lifetime of the herd while meeting the requirements of the farm. The overall accuracy of the system was estimated at 93.4%.

Jiang et al. [12] proposed an SMC estimation approach for mixed soil types based on PCA and machine learning, with hyperspectral data as the input. The R^2 and RMSE of the optimal model were determined as 0.932 and <2%, respectively. This approach proved to be valuable in extracting data on farm entropy prior to the sowing of crops on agricultural land, and provides a basis for the use of hyperspectral imagery to calculate SMC.

Geostationary satellites are able to extract information on the daily variations in crop canopy reflectance based on high-temporal-resolution imagery. Lin et al. [15] proposed the synthetic angle normalization model (SANM), which uses vegetation canopy reflectance as its input. The SANM makes use of the advantages of GSS imaging and is able to quantitatively compare spatiotemporal remote sensing data.

Advanced target recognition algorithm techniques, such as YOLO-, Swin-Transformer-, and Faster-RCNN-based models, have also been developed to identify weeds and diseases for farmland management.

For example, Zhang et al. [14] introduced EM-YOLOv4-Tiny to identify weeds and compared it with six other weed recognition deep learning models, namely YOLOv4-Tiny, YOLOv4, YOLOv5s, Swin-Transformer, and Faster-RCNN. The proposed approach was observed to outperform the majority of the models, with an mAP of 94.54%.

Li et al. [6] developed BTC-YOLOv5s based on YOLOv5s for the detection of apple leaf disease. In particular, the inclusion of the transformer and convolutional block attention modules decreased the background noise.

Intelligent agriculture can achieve information perception, quantitative decision-making, and intelligent control throughout agricultural production by integrating information technologies such as the Internet of Things, big data, artificial intelligence, and intelligent equipment with agriculture. Therefore, interdisciplinary cooperation is necessary for deepening the application of deep learning in intelligent agriculture. These collaborations include expert-assisted data annotation, machine learning methods, the design of agricultural-specific sensors, intelligent drones, intelligent robots, and more. Optical sensors and deep learning are fundamental in data collection, information perception, and decision analyses. Research on their combinations is crucial for promoting the development of intelligent agriculture. Therefore, we hope this work can attract the attention of the agricultural, electronic, and computer communities and promote more research on optical sensors and machine learning. The research published in this Special Issue focus on a variety of machine learning methods, optical sensors, and platforms for agricultural monitoring. The novel results and progress made by the papers will hopefully stimulate further research in these areas.

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