

Editorial

Computational, AI and IT Solutions Helping Agriculture

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This Special Issue, entitled “Computational, AI and IT Solutions Helping Agriculture”, brought together 17 publications, including 16 original research papers [1–16] and 1 review paper [17], addressing advances in precision agriculture on species and diseases detection and monitoring [1,2,6,7,9,11,17], classification [10,12,16], area mapping [14], robotics [5], smart machinery operations [8] and diagnostics [3,4], market predictions [13], and hybrid online platforms [15], as summarized below and shown in Table 1.

In [1], a novel object detection model called Wheat-FasterYOLO was introduced for real-time tracking and counting of wheat ears. The model applied FasterNet [18], a lightweight partial convolution network to enhance reference speed, reduce parameters, and improve the efficiency of object detection. To improve the accuracy and precision of the localization, the object confidence and bounding box regression loss in Wheat-FasterYOLO were based on the SCYLLA intersection over union method [19] instead of traditional intersection over union (IoU) [20]. The bi-level routing attention mechanism BiFormer was used to improve the dynamic extraction of wheat ear features along with reducing the complex background effects. Also, the neural network DCNv2 with deformable convolutions [21] was applied to improve the detection of wheat ears of various characteristics by dynamically adjusting kernel positions. The Feature Pyramid Network in the object detection was elaborated by applying a path aggregation network with content-aware lightweight up-sampling operator CARAFE to reduce the feature loss during up-sampling, thereby better capturing the wheat ear details within the context. Furthermore, the Kalman filter-based target-tracking algorithm OC-SORT was adopted for reliable real-time tracking and counting. The Wheat-FasterYOLO model was trained and validated by the Global Wheat Head Detection dataset and tested in real time by video data captured by drones. By achieving a mean average precision (mAP) of 94.01%, thus surpassing popular object detectors like YOLOX [22] and YOLOv7-Tiny [23], a higher-order tracking accuracy of 60.52%, and a tracking accuracy of 91.88%, Wheat-FasterYOLO appeared to be a promising tool for the detection and counting of wheat ears.

In [2], a deep learning (DL) model was proposed for pest detection on corn crops. The model was designed for low-power devices and tested on two versions of the MobileNet [24] single-shot detector (SSD), a neural network for real-time object detection with limited computational resources. The two versions were MobileNet-SSD-v1 and MobileNet-SSD-v2-Lite used in mobile agricultural systems and tools. The proposed model introduced an innovative two-step transfer learning approach for the detection of various harmful and beneficial beetles. During the first step, the model managed to distinguish the class of harmful beetles named “Beetle” and represented by genera *Anoxia*, *Diabrotica*, *Opatrum*, and *Zabrus* from the class of beneficial beetles named “Ladybug” and represented by genera *Coccinella*. During the second step, the species of the class “Beetle” were recognized properly. The overall performance of the model resulted in enhanced accuracy of mobile device classification and detection of various harmful beetle species while distinguishing them



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from the beneficial ones. Improved MobileNet-SSD-v1 and MobileNet-SSD-v2-Lite scored mAP values of 90.8% and 89.23%, respectively, outperforming the baseline scenarios by >6%. The proposed model demonstrated the potential for mobile applications in low-power systems and devices used in agriculture, e.g., automated counting pest traps, autonomous equipment, or cell phones, thereby contributing to improved corn crop diagnostics.

In [3], a new method and a model were introduced for the fault diagnosis of rolling bearings in agricultural machines based mainly on improving the feature extraction mechanism for image classification in the existing Vision Transformer (ViT) architecture [25]. The method involved obtaining vibration signals from the rolling bearings by acceleration sensors and their preprocessing for noise reduction by singular value decomposition and energy difference spectrum. The preprocessed one-dimensional signal was converted into a two-dimensional time–frequency image by generalized Fourier-based S-transform. The image was further processed with relative position coding by the modified ViT for pattern recognition classification and reporting the final fault diagnosis. In the modified ViT, the original image segmentation mechanism was replaced by ResNet34, a residual deep convolutional neural network (CNN) used to improve feature extraction by reducing model parameters and improving computational efficiency [26]. The above resulted in the proposed SVD-EDS-GST ResViT model, which performed with an average accuracy reaching 99.08%, outperforming existing rolling bearing fault classification CNN- and ViT-based models and demonstrating potential for use in an actual operating environment.

In [4], a multisource data-fusion method with Bayesian optimization based on CNN [27] was introduced as a backbone of an intelligent fault diagnosis system for inter-turn short circuit faults (ITSC) in the permanent magnet synchronous motors of agricultural machinery. Data from different signals were used to construct a synchronized dataset of current and vibration signals. Features from those signals were extracted separately by CNN with dilated convolution [28] for a large receptive field with the same number of parameters and a channel attention mechanism for adjusting the weights of the fault features from different signals and channels. Then feature fusion of the two types of signals was performed, and Bayesian optimization was applied for fine-tuning the hyperparameters while improving the training efficiency and enhancing the model's performance. The proposed method was used in a multi-stream feature fusion model for an ITSC fault diagnosis system, which was tested as a pilot and showed promising results with a validation accuracy of 98.99% and an error loss rate approaching zero.

In [5], a 3D apple detection framework FRESHNet was constructed for the needs of agricultural robotics to identify the apple stem directions during harvesting. A 3D object detection algorithm was proposed for recognizing the dimensions and locations of the apples and their three-axis rotation, following the indoor robotics approach. The PApple_RGB-D-Size [29] dataset was reprocessed for pairing 3D point clouds and 2D images of apples in orchards with label information to annotate the 3D bounding boxes and stem directions. The data of cloud points and images were processed by MinkResNet [30], with sparse convolution and ResNet50+FPN networks, respectively, to extract 3D and 2D features that were fused for the effective integration of geometric details and contextual information. The output was classification, 3D bounding box predictions, and rotating angle predictions for automated harvesting. FRESHNet was trained, validated, and tested, and it demonstrated its potential by achieving an average precision (AP) of 89.56% and average recall of 99.16%.

In [6], an AI-based poultry monitoring system was introduced consisting of a user-friendly web application connected to the YOLOv8 object detection model [31] for processing videos from surveillance cameras installed in chicken coops. The web application was built using the Flask lightweight framework for Python and designed to be accessible by

various edge computing devices. The dataset for training and validation consisted of 1300 images extracted from video recordings from four cameras in a chicken coop, manually annotated and cross-validated. The object detection model was operated using the Ultralytics YOLOv8 framework [32]. Particularly, YOLOv8m (medium) was selected for its advances in dealing with occlusion (object clustering), lighting variation (poor lighting, shadows, reflections), and various image resolutions that might significantly impact detection accuracy. The pilot version precision of 93.1%, recall of 93%, F1-score of 91%, and mAP of 93.1% demonstrated potential for production-level deployment and application.

In [7], five different object detection models were compared for their performance on agave plants of various conditions and shapes to evaluate the best one for application in agriculture. The YOLO family models YOLOv7, YOLOv7-tiny, YOLOv8 [23,33], and Detectron2 library models Faster R-CNN and RetinaNet were selected [34]. A database of 333 digital images of agave plants was created and annotated by VGG image annotator. The plants were assigned to five classes according to their health conditions, color, spotting, and size. All models were trained, validated, and tested under the same conditions and on the same randomly determined partitions of the database in a ratio of 7:1:2, respectively. The obtained AP and mAP suggested that YOLOv7 performed the best, surprisingly outperforming YOLOv8. The findings of this study could be used to refine the future selection of object detection models for agave classification and detection.

In [8], an adaptive root cutting system with machine vision for garlic bulb detection by IRM-YOLO [35] deployed on the Jetson NVIDIA Nano device [36] was introduced for garlic harvesters to address the high cutting injury rates and leakage, and thereby to improve the quality of harvested garlic. The adaptive root cutting harvesting system with its main components, i.e., an electronic control box, a welded harvesting table, a background board, a cutting device, and a blade speed control board, was installed on the 4DSL-7 garlic harvester. Bulb images taken by the cutting device camera were processed to the accompanying edge computing device Jetson Nano, where the bulb detector detected the garlic bulbs by CNN for classification and obtaining the pixel position of the target. This was based on the fact that the cutting device would adjust the knife disk rotation and cutting height. An AP of 99.2% of the bulb detector IRM-YOLO algorithm with a detection time of 0.0356 s signified the potential to expand the bench and field tests to commercial applications.

In [9], a lightweight dual-channel cross-feature fusion attention network architecture DCFA-YOLO was introduced for cherry tomato fruits and bunch detection. DCFA-YOLO was based on the YOLOv8_n object detection model [33] with several optimizations of the backbone network and the neck for improving feature extraction and fusion, and contextual integration, while maintaining reduced computational costs. The C2f module of the original YOLOv8_n was replaced in the backbone by ShuffleNetV2 [37], capable of group convolutions and channel shuffling, and in the cross-feature fusion neck by C2f_RepGhost [38]; an SPPF_CBAM attention mechanism was added too. DCFA-YOLO was trained on greenhouse cherry tomato images, and ablation tests were implemented to study the effects of the above optimizations. DCFA-YOLO performed better than single-modal networks and other fusion-based networks in terms of its RGB color, depth dual modality, and optimizations. Indeed, with a precision of 94.9%, recall of 91.4%, and F1-score of 93.1%, DCFA-YOLO outperformed many YOLO- and SSD-based networks.

In [10], a new dataset PDPQCD for the classification of potato pest and disease queries was constructed based on prompt engineering and large language models (LLMs). Also, a question classification model GF-CNN utilizing gated fusion was introduced for optimizing text feature extraction. Using ChatGPT 4 as the LLM, lists of diseases, templates, and questions were initialized for the new dataset containing 20,260 entities. A pre-trained

BERT model [39] with dynamic word embeddings was incorporated in GF-CNN, together with a gating fusion mechanism to control simultaneous max-pooling and average pooling for leveraging local and global important features, and the softmax activation function was used for probability distribution in multi-class classification tasks. The PDPQCD dataset was tested by seven BERT-based models [40,41], which all achieved precision, recall, and F1-scores > 98% as GF-CNN performed the best. GF-CNN confirmed its high-level performance with ablation experiments on PPDQCD and two other datasets: Subj in English and THUCNews in Chinese.

In [11], a novel DL framework DHS-YOLO was introduced for detection by the unmanned aerial vehicle (UAV) of slender wheat seedlings, based on the YOLOv11 object detection model [42]. DHS-YOLO implemented three strategic improvements: a Dynamic Slender Convolution (DSC) block to extract the flexible and slender features of wheat seedlings by deformable convolution [21], a Histogram Transformer (HT) attention block to filter out irrelevant features and illumination-induced image degradation, and the ShapeIoU loss function to strengthen the geometric consistency between predicted and ground-truth bounding boxes; they were implemented in the framework's backbone and neck. Thus, the slow deformable convolutions by DSC were compensated by the dynamic-range HT attention, resulting in reliable head detections. DHS-YOLO was trained, validated, and tested in a series of ablation experiments using UAV-captured image datasets of varying illumination intensities, and it scored a precision value of 94.1%, recall of 91.0%, and mAP of 95.2%, outperforming other models and the baseline YOLOv11.

In [12], a public image database for three plant diseases and a family of segmentation networks, PDSNets, were introduced for plant disease estimation. The image datasets for soybean bacterial blight (SBB), cedar apple rust (CAR), and wheat stripe rust (WSR) were obtained from public resources or collected in the field. Pixel-level annotation for SBB, CAR, and WSR included background (B), healthy leaf (H), and disease spots (S) pixel classes. The PDSNets family consisted of three versions, PDSNetx1.0 and the lighter PDSNetx0.75 and PDSNetx0.5, based on LinkNet [43] with the ResNet-18 encoder and decoder with a pixel-level classifier. In total, 60% of the dataset for each disease was used for training and 40% for testing. Ablation experiments with PDSNetx1.0 resulted in outperforming the other models, including the baseline LinkNet. All three versions outperformed U-Net [44], DeepLabV3+(ResNet-18) [45], and LinkNet with F1-scores > 98%, 93%, 86% and IoU > 97%, 87%, 76% for B, H, S pixel classes, respectively, showing the potential for commercial use.

In [13], a DL model with the attention mechanism STL-LSTM-ATT-KAN was proposed for predicting ginger price as follows. The Seasonal Trend Decomposition module was implemented to decompose the price time series into trend, seasonal, and stochastic components, which were used by a long short-term memory recurrent neural network to capture long-term dependencies. The Adaptive Multi-Particle Swarm Optimization algorithm [46] was applied to optimize model parameters. The model used 13 independent variables and ginger price time series from 2014 to 2024. The aggregated dataset was split for training, validation, and testing in a ratio of 65:20:15. STL-LSTM-ATT-KAN outperformed seven other models, reaching mean average error (MAE), mean square error (MSE), root mean square error (RMSE), and coefficient of determination (R^2) values of 0.111, 0.021, 0.146, and 0.998, respectively, demonstrating its potential for commercial application.

In [14], a novel image data structure and a spatial-spectral fused attention CNN network SSFAN for image processing [47] were introduced for mapping *Torreya grandis* areas in China. Multiple Sentinel-2 Level -1C images [48] taken in 2023 were processed to obtain 13 spectral bands, 6 vegetation indices, and 6 texture indices, resulting in a dataset of 12 synthesized monthly images of 300 bands and 215,640 pixels. The latter were split into training, validation, and test sets in a 60:20:20 pixel ratio. The maximum

redundancy maximum relevance algorithm was applied to select the optimal bands. They were processed by the two branches of SSFAN to produce spectral and spatial feature maps, which were fused to predict *Torreya grandis* areas. The method achieved overall accuracy of 99.1% and a Kappa coefficient of 0.961, demonstrating its potential to leverage the satellite multispectral feature extraction with limited spatial and spectral resolution.

In [15], a hybrid AI-driven architecture AGRARIAN was introduced to leverage the centralized cloud infrastructure of smart farming platforms by using localized edge processing, federated AI models, and hybrid 5G/satellite connectivity [49,50] for various agriculture environments, including those with infrastructure constraints. AGRARIAN horizontal functionality via customer portal, decision support systems, platform infrastructure, and external data sources was implemented via four vertical layers. The sensor layer comprised environment, soil, and livestock data acquisition through ground, UAV, Internet of Things (IoT) sensors, meteorological stations, satellite observations, and tracking devices. The network layer enabled 5G, satellite, and edge and ground communication between sensors, computing nodes, and cloud-based systems for seamless connectivity. The data processing layer acted as a computational hub and the application layer provided services to farmers, policymakers, and researchers, such as decision support and monitoring systems, crop forecasting, smart irrigation and water management, disease and pest alerts, and blockchain-enabled goods logistic traceability. The above functionality showed a perspective for interconnecting with online platforms for process-based, machine learning (ML), and IoT modeling [51–53]. Pilot scenarios demonstrated AGRARIAN's potential for irrigation control, crop disease, and livestock monitoring.

In [16], a lightweight DL framework AgriFusionNet was introduced for multisource plant disease classification and modeling. AgriFusionNet was built upon EfficientNetV2-B4 CNN [54], enhanced by Fused-MBConv blocks and implemented by Adam optimizer and Swish activation for more efficient training and model generalization. By the fusion of the large image collection PlantVillage [55], RGB, and multispectral drone images, and IoT sensor data on temperature, humidity, and soil moisture, a multimodal dataset was tailored and augmented for extending the diagnosis of diseases to their prediction under various agriculture conditions. The dataset was split for training, validation, and testing in a 70:20:10 ratio, and AgriFusionNet showed its potential by 94.3% classification accuracy with 30% less parameters than other comparable methods.

In [17], an extensive review was made of existing and emerging crop management technologies for smart and precision monitoring on germination, water status, nutrient stress, diseases and weeds detection, chlorophyll estimation, crop protection, and yield. The study overviewed Agriculture 4.0 crop monitoring and management technologies based on AI, ML, DL, and IoT with 5G and cloud computing environment [56–58]. They were situated in a perspective towards Agriculture 5.0 technologies of the next level [59–61], based on robotics, digital twins, UAV, unmanned ground vehicles (UGVs), blockchain, and big data analytics with 6G and fog and edge computing, as the advances and challenges were analyzed.

Thus, the contributions of this Special Issue could be seen within the perspectives of the transition of AI, ML, and DL technologies from Agriculture 4.0 to Agriculture 5.0. These perspectives include, but are not limited to, the following: (i) technical development and elaboration of those technologies, e.g., improving CNN with newly introduced or adapted attention mechanisms and/or activation functions; (ii) application expansion to various agriculture activities; (iii) upgrading to more sophisticated technologies and autonomous systems, e.g., from cloud computing to localized fog and edge computing and from classification and object detection to 3D object detection, robotics, smart machinery operations, and diagnostics.

Table 1. Summary of research items.

Item	Application Types	Agricultural Activities	Outcomes
[1]	YOLO-based computer application	Real-time tracking and counting of wheat ears	Object detection model
[2]	SSD-based mobile application	Pest beetle detection on corn crops	Object detection model
[3]	CNN-based vision transformer architecture	Diagnosis of rolling bearings in agricultural machines	Machinery fault diagnostics system
[4]	Multi-stream feature fusion architecture	Diagnosis of short circuit faults in permanent magnet synchronous motors in agricultural machinery	Machinery fault diagnostics system
[5]	3D object detection framework for agricultural robotics	Automated apple harvesting	3D object detection model
[6]	YOLO-based monitoring framework	Poultry monitoring	Object detection model within a web application
[7]	YOLO and Detectron2-based computer applications	Agave plants classification and detection	Object detection models, comparative study
[8]	YOLO-based application for agriculture machines	Automated garlic harvesting	Machine vision device for automated harvesters
[9]	YOLO-based computer application for agricultural robotics	Cherry tomato fruits and bunch detection.	Object detection model
[10]	CNN-based computer application	Potato pests and disease classification	Dataset and classification model
[11]	YOLO-based framework for UAV	Detecting wheat seedlings	Object detection model
[12]	LinkNet-based computer application	Plant disease estimation	Three datasets and segmentation networks
[13]	LSTM-based computer application	Ginger price prediction	DL model
[14]	Data structure and image processing CNN	Torreya grandis area prediction	Area mapping tool
[15]	Hybrid AI-driven architecture	Crops, irrigation and disease management and control, livestock monitoring	Smart farming services
[16]	CNN-based computer application	Plant disease diagnosis	Dataset and classification and prediction model
[17]	Review	Agriculture 4.0 and 5.0 crop management technologies in monitoring	Summary

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