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*Editorial*
# Internet and Computers for Agriculture

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The Special Issue "Internet and Computers for Agriculture" reflects the rapidly growing need for new information and communication technology (ICT) involvement in agriculture which is changing globally. The aim was to cover the recent and current progress in various aspects of ICT applications in precision agriculture, such as web applications and mobile apps, Internet of Things (IoT) platforms and smart devices, cloud technologies, artificial intelligence (AI), machine learning (ML), and deep learning (DL)-based solutions via neural networks (NNs) and convolutional neural networks (CNNs) for detection, classification, computer/machine vision, and language processing purposes, as well as for scientific modeling in agriculture and natural ecosystems. This Special Issue brought together twenty peer-reviewed articles, including eighteen original research articles, [1–18] (chronologically presented), one case report article, [19], and one review article, [20], as summarized in Table 1 and described below.

In article [1], a novel CNN-based DL method for grape variety identification was proposed based on the canonical correlation analysis (CCA) applied to fuse selected deep features from various CNNs, i.e., AlexNet, GoogLeNet, ResNet18, ResNet50, and ResNet101, and a multi-class support vector machine (SVM) classifier trained in these fused features. To test the proposed method, grape images from the open-source Embrapa Wine Grape Instance Segmentation Dataset (WGISD) were initially resized to meet the CNN requirements and then used for selected deep feature extraction. In general, the fused deep feature approach outperformed the single deep feature approach, as indicated by the best performance of the former (AlexNet and ResNet50) with an $F_1$ score of 96.9% compared to the best performance of the latter (ResNet101) with an $F_1$ score of 88.2%. The proposed method can be applied in developing the computer/machine vision of smart machinery for a more targeted and accurate identification of grape varieties, thus improving grape yield.

In article [2], an adversarial contextual embeddings-based model for agricultural diseases and pests (ACE-ADP) was proposed to be implemented as a web application for named entity recognition in Chinese agricultural diseases and pests domains (CNER-ADP). While the adversarial training enhanced the robustness of identifying rare named entities, the ACE-ADP dealt with the polysemous issues (multiple meanings of the same word) and quality of text representation by fine-tuning the bidirectional encoder representations for transformers (BERT) ML framework, a neural-network-based technique originally developed by Google for natural language processing (NLP). Thus, the multi-vector BERT-based ACE-ADP performed better by 4.23%, reaching an $F_1$ score of 98.31%, compared to the single-vector baseline word2vec-based BiLSTM-CRF model when both applied to the Chinese named entity recognition dataset for agricultural diseases and pests (AgCNER).

In article [3], a novel, end-to-end, AI-powered, IoT-based platform and agro-weather station were introduced into smart farming. The multi-agent agile and containerized system consisted of low-cost hardware and software components, organized in five layers, for continuous real-time monitoring and AI-based forecasting of various meteorological factors, e.g., air temperatures (minimum, maximum), humidity, pressure, precipitation, wind speed, and dew point. These meteorological factors were surveyed by heterogeneous nodes, located at the base station and at various distances from it, thereby constituting the

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perception back-end layer of various sensors. The collected data were transmitted to the local webserver (Apache) for pre-processing and to the cloud server for backup using the transmission back-end layer, tasked with ensuring the wired and wireless communication of heterogeneous protocols, e.g., MQTT, NRF24L01, HTTP, and WiFi. To spare resources in the local webserver, Cronjob was run to send series of measurements from the database to Google Collaboratory free computing resources (Colab), where the AI-based predictions of meteorological factors were conducted using ML regression methods on the TensorFlow framework, using the Keras neural network library, optimizer Adam, and the mean squared error (MSE) as a loss function. Upon completion of model training using Keras, Colab would generate a TensorFlow Lite (tflite) outcome to be sent back to the base station and be used by the local webserver for AI modeling embedded within the platform website. The middleware back-end layer was designed to orchestrate the performance of all agents, including the virtual private network (VPN) and the database. The two front-end layers with user-friendly web-based graphical user interfaces (GUIs) formed the presentation layer for reporting weather observations and AI-based predictions to different users based on their personal profiles, and the purpose of the management layer was for operation and maintenance. The agro-weather station was successfully tested in Casablanca, Morocco, with mean absolute scale error (MASE), root mean square deviation (RMSE), and Willmott's index of agreement stabilizing after the fifth epoch of AI modeling at 0.0012, 0.034, and 0.987, respectively.

**Table 1.** Summary of presented research.

| Article | Implemented Application Types | Agricultural Activities | Outcomes |
|---|---|---|---|
| [1] | AI application (DL and CNN) | Grape variety identification | Computer/machine vision |
| [2] | Web application, AI application (NN) | Disease and pest name recognition | Natural language processing system |
| [3] | Web application (cloud-based), IoT platform, AI application (ML) | Weather measurements and prediction | Meteorological station |
| [4] | AI application (DL and CNN) | Maize variety seed recognition and classification | Computer/machine vision |
| [5] | Modeling software | Quantifying uncertainties in modeling hydrology | Decision support system |
| [6] | Modeling software | Product distribution | Transport optimization system |
| [7] | Mobile app, modeling software | Farm management | Information system |
| [8] | AI application (DL and CNN) | Grape disease recognition and classification | Computer/machine vision |
| [9] | AI application (DL and CNN) | Fishery product price prediction | Forecasting system |
| [10] | Web application (cloud-based), mobile app, IoT platform | Collecting soil, air, and light properties | Smart monitoring system |
| [11] | Web application (cloud-based), modeling software | Predicting olive crop yield | Management and decision making system |
| [12] | AI application (DL and CNN) | Grape detection | Computer/machine vision |
| [13] | AI application (DL and CNN) | Buffalo breed recognition and classification | Computer/machine vision |
| [14] | AI application (DL and CNN) | Tea picking | Computer/machine vision |

**Table 1.** *Cont.*

| Article | Implemented Application Types | Agricultural Activities | Outcomes |
|---|---|---|---|
| [15] | Modeling software | Agricultural e-commerce | Behavior system |
| [16] | AI application (DL and CNN) | Monitoring duck flocks | Real-time detection system |
| [17] | IoT application | Measuring environmental, Plant, and soil water status | Monitoring system |
| [18] | Modeling software | Planning uncertainties in horticulture market | Decision-making system |
| [19] | Modeling software | Selecting leisure agricultural parks | Intelligence approach |
| [20] | Review | Digital technologies in agriculture | Summary |

In article [4], the open-source software framework PyTorch was used to build upon the existing ResNet CNN [21] and to create a P-ResNet network with 17,960,232 parameters, optimizer Adam, batch normalization between convolutions, and rectified linear unit (ReLU) during training. P-ResNet models were developed using PyCharm Integrated Development Environment (IDE) and were trained for classification using a server with NVIDIA GeForce GTX 1660 SUPER GPU and 16 GB GDDR4 on-board memory. The proposed DL network was intended to be used in machine/computer vision tasks, particularly in the classification of various seeds. Thus, P-ResNet was applied to the classification of seeds of five main maize varieties in China, i.e., BaoQiu, ShanCu, XinNuo, LiaoGe, and KouXian, by using 6464 RGB images for training and 1616 ones for validation. According to classification accuracy, P-Resnet outperformed well-known DL networks, such as AlexNet, VGGNet, GoogLeNet, MobileNet, and DenseNet, by several percentage points.

In article [5], a multi-model hydrological framework decision support system (DSS) was proposed to deal with water security modeling in the context of environmental sustainability and climate resilience. As water supply is critical to life on Earth and soil water contents are key controls in many biogeochemical processes in natural and modeled ecosystems [22], the DSS was applied to quantify the uncertainty in inputs of various hydrological models in order to improve their climate resilience. The water security modeling was coupled to food security in different model development scenarios. As a result, a four-dimensional dynamic space mapping source, resource availability, infrastructure, and economic options were suggested to capture the climate resilience phenomenon. The outcomes of the DSS can be made available to farmers to help with sustainable food production. The proposed DSS was tested for four catchments in Australia.

In article [6], a model for timely management of the distribution of various agricultural products was introduced to enhance the benefits and satisfaction that both agriculture producers and consumers experience. The proposed model was based on solving the time-dependent, split delivery green vehicle routing problem with multiple time windows (TDSDGVRPMTW) for both economic cost and customer satisfaction purposes, and thus could be seen as a modern version of the transportation math problem in contemporary agriculture. The objective to minimize the sum of the economic cost and maximize average customer satisfaction was achieved by optimizing time-varying vehicle speeds, fuel consumption, and carbon emissions in multiple time windows. Applying the model with real data from China suggested reduced total distribution costs, balanced energy conservation, and improved customer satisfaction.

In article [7], a mobile app on an Android application interface platform was introduced to farm management information system (FMIS) services to assist farmers in managing their farms. To reduce the price of and enhance the access to FMIS services, a new conceptual FMIS model for farm efficiency was proposed based on identifying commodity and research areas, and performing information needs assessments. The new model consisted of five layers for information needs, data quality assessment, data extraction, split, match and merge (SMM) processes, and presentation. The new FMIS model was used to address the needs of smallholder chili farmers in Indonesia and outlined areas for improvement in FMIS services.

In article [8], a novel lightweight CNN GrapeNet was introduced to deal with inherent difficulties in identifying crop diseases at different stages due to their wide gamut of symptoms and various plant tissues and color changes. GrapeNet was designed as a modern deep network of residual blocks and convolutional block attention modules (CBAMs) for extracting rich features and key disease information. Special residual feature fusion blocks (RFFBs) were introduced to achieve feature fusion at different depths, the article are dealing with vanishing gradient issues of ultra-deep networks [23]. Identification accuracy of GrapeNet outperformed other deep networks, such as ResNet34, DenseNet121, MobileNetV2, MobileNetV3_large., by ~1.5 to 4 percentage points, while the training time of GrapeNet decreased due to a reduced number of parameters. GrapeNet was tested for grape leaves of the AI challenger 2018 dataset.

In article [9], a recurrent neural network (RNN)-based long short-term memory (LSTM) model was coupled with a novel adaptive signal decomposition method, called variational modal decomposition (VMD), and a new improved bald eagle search algorithm (IBES) to propose the innovative fishery product price forecasting model VMD-IBES-LSTM, capable of dealing with time series data efficiently. Compared to other ML forecasting models, VMD-IBES-LSTM showed high prediction accuracy and better explained the seasonality and trends of changes in China's aquatic product consumer price index. Thus, VMD-IBES-LSTM was shown to be an effective tool for addressing management and decision-making tasks related to predicting the aquatic product consumer prices in China.

In article [10], a cloud-based web application interconnected to an IoT smart system was introduced to address the needs of rural farmers in Pakistan in an attempt to overcome the illiteracy-related absence of proactive decision making in all phases of crop production. The smart system was connected to accessible devices and sensors for real-time capturing of soil moisture, temperature, pH, light intensity, and air humidity. The system was designed to help farmers understand environmental factors related to soil fertility, suitable crop cultivation, automated irrigation, harvest schedule, pest and weed control, crop diseases, and fertilizer usage. The system was upgraded to a mobile app for bilingual usage, i.e., in 'Urdu' and 'English', and was equipped with visual, audio, and voice components as well as iconic and textual menus designed for farmers of various literary levels.

In article [11], predictive software was proposed for management and decision-making purposes in profitability and the economic balance of agricultural farms. The software consisted of a cloud-based web application with a nested user-friendly model for predicting crop yields based on different ML regression algorithms, such as the generalized linear model (GLM), and the Gaussian and Linear kernel support vector machine (SVM). As part of the training, the model was fed more than 20 spatio-temporal meteorological parameters and data for the yields of eight consecutive years. The proposed software performed well in the early prediction of crop yield with absolute errors being less than 20%. The results were crucial for decision making related to tillage investments and crop marketing. The web application was tested on an olive orchard in Spain.

In article [12], a novel method for grape detection was proposed related to computer/machine vision. The method was based on the lightweight network Uniformer, capable of capturing long-range dependencies while improving feature extraction, and the bi-directional path aggregation network (BiPANet), capable of fusing low- and high-resolution feature maps for optimizing semantic and detailed information. The reposition non-maximum suppression (R-NMS) algorithm improved the localization accuracy, and the novel cross-layer feature enhancement strategy in BiPANet resulted in a significant reduction in the number of parameters and computational complexity. The novel method for grape detection outperformed other CNN-based algorithms for computer vision, such as YOLOx, YOLOv4, YOLOv3, Faster R-CNN, SSD, RetinaNet, and the mAP. The proposed method was tested on grape datasets from China.

In article [13], a self-activated multilayered CNN, consisting of five blocks of convolution, batch normalization, ReLU activation function, and max pooling, was proposed as a computer-vision-based recognition framework to identify different buffalo breeds. Particularly, the Nili-Ravi breed, one of the best worldwide for milk and meat production, was successfully identified from other breeds in an attempt to satisfy the great demand for breed selection and breed production. All seven of the classifiers that were tested and compared for breed identification, i.e., Fine-KNN, Med-KNN, Coarse-KNN, LP-Boost, Total-Boost, Bag-Ensemble, and the support vector machine (SVM), performed well and managed to recognize and classify the Nili-Ravi breed from the Khundi breed and a miscellaneous class of other buffalo breeds. The accuracy of identification reached 93% for the CNN performance with the SVM classifier and exceeded 85% for the other classifiers. The CNN framework was tested in Pakistan.

In article [14], a lightweight CNN, named MC-DM (Multi-Class DeepLabV3+), was proposed as a computer vision approach for tea sprout segmentation and picking point localization, based on improved Mobile Networks Vision 2 (MobileNetV2) with an inverted residual structure [24]. The MC-DM architecture allowed for a reduced number of parameters and calculations. In addition, an image dataset of high-quality tea sprout picking points was built to train and test the MC-DM network. The atrous spatial pyramid pooling module in MC-DM acted to obtain denser pixel sampling for the purpose of enhancing the accuracy of picking point identification, which reached 82.52%, 90.07%, and 84.78% for a single bud, one bud with one leaf, and one bud with two leaves, respectively. The MC-DM has been proposed and tested as an effective method for fast segmentation and visual localization for automated machine picking of tea sprouts in China.

In article [15], e-commerce interest linkage mechanisms were studied using the theory of planned behavior and the evolutionary game model involving the causal relationship between farmers' characteristics, experiences, cognition, behaviors, and willingness, and government policies. The influence of government policies on farmers' cognition, participation, and behaviors surrounding e-commerce interest linkage mechanisms were studied using the structural equation model. The results showed that the basic characteristics and experiences of farmers affected their cognition surrounding e-commerce interest linkage mechanisms, their willingness to participate, and the way in which they behave in e-commerce activities. While government policies had a positive effect on farmers' cognition surrounding e-commerce, it was found that they did not directly stimulate farmers to participate. Despite this, government policies and farmers' basic characteristics interacted and acted together when it came to willingness to participate and the behavior of farmers in e-commerce. The proposed methodology was tested in China.

In article [16], a CNN-based DL algorithm was proposed for real-time monitoring of dense hemp duck flocks as an alternative to manual duck counting in the intelligent farming industry. Particularly, the authors applied a modified YOLOv7 DL algorithm for the recognition and detection of moving objects in real time. The YOLOv7 algorithm has been further improved by implementing a convolutional block attention module (CBAM) for feature extraction, which can perform attention operations in the channel and spatial dimensions. A large-scale image dataset consisting of 1500 hemp ducks was introduced for the purposes of full-body frame labeling and head-only frame labeling. The results showed that CBAM-YOLOv7 had outstanding precision. The comparison between the two labeling methods demonstrated that the head-only labeling method resulted in a loss of feature information, while the full-body frame labeling method appeared to be better suited to detection in real time. The proposed algorithm was tested in China.

In article [17], the LoRaWAN point-to-multipoint networking protocol was used for implementing an IoT application of sensors for inexpensive and continuous monitoring of environmental, plant, and soil water status in a vineyard. Results showed that the IoT system communicated data continuously and without loss. LoRaWAN was already known as an alternative with reduced cost and superior range compared to WiFi and Bluetooth. Its importance in IoT was justified by its applicability to resource management in a time of global change, especially in remote, rural areas where cellular networks have little coverage and 5G networks of prohibitive costs still lack infrastructure. The IoT system was tested in Portugal.

In article [18], MAXQDA software for qualitative and mixed-methods data was used to investigate the planning uncertainties and to provide data-driven support in the decision-making process along the supply chain of horticultural companies for ornamental plants, perennials, and cut flowers. Real-life planning issues were explored by interviewing experts and the management of typical companies operating in the market. The results showed that tactical planning domains of material/product requirement and production and demand planning are especially critical for the market. An outstanding need emerged for practically developing relevant decision support systems, in addition to some existing ones of a limited extent that were not fully compatible with marketing requirements in the horticultural sector. The methodology was tested in Germany.

In article [19], a case report was presented proposing a fuzzy collaborative intelligence (FCI) approach for selecting leisure agricultural parks during times of great restrictions, such as the recent COVID-19 pandemic. The novelty of the proposed approach was in combining the asymmetrically calibrated fuzzy geometric mean (acFGM), fuzzy weighted intersection (FWI), and fuzzy Vise Kriterijumska Optimizacija I Kompromisno Resenje (fuzzy VIKOR) function. The approach was tested for Taiwan and showed that agricultural parks were among the favorite locations for traveling for leisure during the COVID-19 pandemic.

In article [20], a review was conducted on the impact of new information and communication technologies (ICT) on sustainable food systems (SFSs) and their transformation in the context of global food security and nutrition. The main focus was on digital agriculture technologies involving IoT, AI, and ML, such as drones, robots, autonomous vehicles, and advanced materials, as well as various gene technology, such as biofortified crops, genome-wide selection, and genome editing. Eight action initiatives were suggested, which coupled to appropriate incentives, regulations, and permits, and would be expected to critically influence adoption and usage of modern technologies for promoting various SFS types.

All of the above original research demonstrated the potential for worldwide application in corresponding or similar domains. The contributions of this Special Issue may be seen in the background of a rapidly growing human population with needs surrounding sustainable and secure food production, water management, and reduced GHG emissions, which clarify the need for smart agriculture solutions as an imminent priority on a planetary scale.

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