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Editorial

Deep Learning Techniques for Agronomy Applications

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Abstract: This editorial introduces the Special Issue, entitled "Deep Learning (DL) Techniques for Agronomy Applications", of Agronomy. Topics covered in this issue include three main parts: (I) DL-based image recognition techniques for agronomy applications, (II) DL-based time series data analysis techniques for agronomy applications, and (III) behavior and strategy analysis for agronomy applications. Three papers on DL-based image recognition techniques for agronomy applications are as follows: (1) "Automatic segmentation and counting of aphid nymphs on leaves using convolutional neural networks," by Chen et al.; (2) "Estimating body condition score in dairy cows from depth images using convolutional neural networks, transfer learning, and model ensembling techniques," by Alvarez et al.; and (3) "Development of a mushroom growth measurement system applying deep learning for image recognition," by Lu et al. One paper on DL-based time series data analysis techniques for agronomy applications is as follows: "LSTM neural network based forecasting model for wheat production in Pakistan," by Haider et al. One paper on behavior and strategy analysis for agronomy applications is as follows: "Research into the E-learning model of agriculture technology companies: analysis by deep learning," by Lin et al.

Keywords: deep learning for agronomy applications; crop growth prediction; pest disaster prediction; drought disaster prediction; flooding disaster prediction; typhoon disaster prediction; cold damage prediction

1. Introduction

In recent years, the techniques of deep learning (DL) have been more popular for application in various agronomy applications. These techniques can be used to support the prediction and prevention of pest disasters, drought disasters, flooding disasters, typhoon disasters, cold damages, and other agricultural disasters. Furthermore, crop growth models can be also built by these techniques [1–8]. For instance, supervised learning techniques (e.g., neural network (NN) [9–13], convolutional neural network (CNN) [14–18], recurrent neural network (RNN) [19–23], and ensemble neural networks (ENN) [24–28]) can be used to forecast weather information and crop growth to improve crop quantities and reduce disaster damage. Furthermore, unsupervised learning techniques (e.g., auto-encoder (AE) [29–33], de-noise auto-encoder (DAE) [34], restricted Boltzmann machine (RBM) [35,36], deep belief network (DBN) [37,38], and deep Boltzmann machine (DBM) [39,40]) can be used to represent data and reduce dimensions for regulation and overfitting prevention. The combination of supervised learning and unsupervised learning techniques can provide the precise estimation and prediction for agronomy applications. Therefore, the aim of this Special Issue is to introduce the readers to a number of papers on various disciplines of agronomy applications.

This Special Issue received a total of 11 submitted papers with only 5 papers accepted. A high rejection rate of 54.55% of this issue from the review process is to ensure that high-quality papers with significant results are selected and published. The statistics of the Special Issue are presented as follows.

- Submissions (11);
- Publications (5);
- Rejections (6);
- Article types: research article (5).

The distribution of authors' countries is showed as follows.

- China (7);
- Pakistan (2);
- Argentina (1).

Topics covered in this issue include three main parts: (1) DL-based image recognition techniques for agronomy applications, (2) DL-based time series data analysis techniques for agronomy applications, and (3) behavior and strategy analysis for agronomy applications. The three topics and accepted papers are briefly described below.

2. DL-based Image Recognition Techniques for Agronomy Applications

Three papers on DL-based image recognition techniques for agronomy applications are as follows: (1) "Automatic segmentation and counting of aphid nymphs on leaves using convolutional neural networks," by Chen et al. [41]; (2) "Estimating body condition score in dairy cows from depth images using convolutional neural networks, transfer learning, and model ensembling techniques," by Alvarez et al. [42]; and (3) "Development of a mushroom growth measurement system applying deep learning for image recognition," by Lu et al. [43].

Chen et al. from China, in "Automatic segmentation and counting of aphid nymphs on leaves using convolutional neural networks", considered that the leaf veins or lesions could be misclassified as pests by color thresholding methods. Therefore, a CNN method based on U-Net was proposed to segment and count aphid nymphs on leaves for aphid detection and avoidance. In experiments, 102 aphid nymph images in practical experimental environments were collected and analyzed to detect the number of aphid nymphs on each image for the evaluation of the proposed method. The results showed that the mean count error and F1-score of the proposed method were 1.2 and 0.9606, respectively [41].

Alvarez et al. from Argentina, in "Estimating body condition score in dairy cows from depth images using convolutional neural networks, transfer learning, and model ensembling techniques" considered that the image recognition techniques could be used to estimate body condition scores for the measurement of obesity degree. Therefore, a CNN method based on transfer learning and ensemble modeling techniques was proposed to extract and transfer the learned features to target ensembling networks for classification. In experiments, 1661 cow images in practical experimental environments were collected and analyzed to estimate the body condition score of each cow for the evaluation of the proposed method. The results showed that both accuracy and F1-score of the proposed method were 0.97 [42].

Lu et al. from China, in "Development of a mushroom growth measurement system applying deep learning for image recognition", considered that the image recognition techniques could be used to estimate the growth rate, quantity statistics, and size classification of mushrooms for developing the growth measurement system of mushrooms. Therefore, a CNN method with anchor boxes that were clustered by K-Means algorithm was proposed to recognize images with different sizes for detecting mushrooms. In the experiments, 500 mushroom images in practical experimental environments were collected and analyzed to detect mushrooms and estimate the size classification of mushrooms for the evaluation of the proposed method. Furthermore, the harvest time could be estimated in accordance with observations of the size classification of mushrooms. The results showed that the average harvest time error of the proposed method was 3.7 hours [43].

3. DL-Based Time Series Data Analysis Techniques for Agronomy Applications

One paper on DL-based time series data analysis techniques for agronomy applications is as follows: "LSTM neural network based forecasting model for wheat production in Pakistan," by Haider et al. from Pakistan [44]. The study considered that the auto-regressive integrated moving average (ARIMA) models could not be used to solve nonlinear problems for the analyses of time series data. Therefore, a LSTM (long short-term memory) neural network method with a data pre-processing smoothing mechanism, which included a smoothing function to smooth out the curve values, was proposed to predict wheat production. In the experiments, wheat production data from 1902 to 2018 were collected and analyzed to predict wheat production for the evaluation of the proposed method. The results showed that the root mean squared error of the proposed method was 792 thousand tons with an improvement of 25% against the existing benchmark models (i.e., ARIMA models) [44].

4. Behavior and Strategy Analysis for Agronomy Applications

One paper on behavior and strategy analysis for agronomy applications is as follows: "Research into the E-learning model of agriculture technology companies: analysis by deep learning," by Lin et al. from China [45]. The study explored the key success factors of augmented reality (AR) and DL adoption for agriculture technology companies. Therefore, the study combined three theoretical frameworks, which included (1) an information system success model, (2) expectation confirmation theory, and (3) the theory of reasoned action for behavior and strategy analyses. In the experiments, 463 effective questionnaires were collected and analyzed to verify 16 assumed hypotheses. The results presented three insights: (1) AR e-learning using DL is a successful model; (2) the strategy of using AR e-learning could be welcomed by employees in the agricultural technology industry; and (3) the development of agricultural and fishery enterprises in Pescadores could be assisted by the Ashoka Foundation [45].

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