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Editorial

Combining Machine Learning Algorithms with Earth Observations for Crop Monitoring and Management

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Combining machine learning algorithms with Earth observations has great potential in the context of crop monitoring and management, which is essential in the face of global challenges related to food security and climate change. The integration of advanced technologies such as digital imaging, satellite data and drone imagery is becoming crucial to better understand the mechanisms that regulate plant growth and development [1–3]. These cutting-edge approaches not only optimize conditions for crops but also enable the early detection of abnormal situations that can trigger non-standard plant defense responses. Advances in machine learning algorithms, combined with a vast database of Earth observation data, are creating unique opportunities to monitor crop growth, health, and yield at various scales. By integrating machine learning with spatial data, precise assessments of crop health can be achieved, which, in turn, fosters the development of innovative strategies to increase productivity and sustainability in agriculture [4]. In this Special Issue, we present research that not only demonstrates the applicability of these technologies, but also reveals their limitations and the critical challenges that need to be addressed to increase their effectiveness in practice [5,6].

We invite readers to explore articles that examine a variety of topics, ranging from an integrated approach to the use of machine learning algorithms in crop monitoring and management. These studies highlight both the practical applications and benefits of these innovative methods, contributing to the advancement of sustainable agricultural practices.

The first article explores the application of machine learning techniques to detect pests and diseases in crops, a significant challenge leading to significant yield losses worldwide [7]. The study focuses on the integration of machine learning models, particularly convolutional neural networks (CNNs), which have shown high performance in accurately identifying and classifying plant diseases from images. An analysis of the literature published between 2019 and 2024 summarizes common methods, covering the steps of data acquisition, preprocessing, segmentation, feature extraction and prediction, leading to the development of robust ML models. The results indicate that the use of advanced image processing and ML algorithms significantly improves disease detection capabilities, resulting in the earlier and more accurate diagnosis of crop disorders. Furthermore, CNN-based models, especially with ResNet architecture, dominate the research, highlighting their popularity in tasks requiring deep architectures and advanced feature extraction [8].

Yu et al.'s [9] research presents the LP-YOLO framework, an optimized lightweight object detection model designed specifically for identifying pests using mobile devices. It describes innovative components, such as LP_Unit and LP_DownSample, which effectively

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replace many of the standard modules found in the YOLOv8 architecture. In addition, the framework includes a novel attention mechanism known as ECSA (Efficient Channel and Spatial Attention), enhancing model detection capabilities. Comprehensive tests conducted on the IP102 dataset confirmed the performance of LP-YOLO, achieving an impressive 70.2% reduction in parameters along with a 40.7% increase in frames per second (FPS). These results highlight the significant effectiveness and efficiency of the LP-YOLO model, demonstrating its potential for real-time pest identification in resource-constrained environments.

The third paper used a drone-mounted multispectral sensor to assess disease severity in soybean at stage R7 [10]. The study applied the random forest classification algorithm to categorize defoliation levels, indicating that combining multispectral imagery with machine learning algorithms allows for a more accurate assessment of Asian rust disease in commercial soybean fields. The random forest algorithm achieved high classification performance with accuracy, precision, recall, F1, specificity and AUC values of 0.94, 0.92, 0.92, 0.92, 0.92, 0.97 and 0.97, respectively.

In Silva et al.'s research [11], correlations between the biometric parameters of forage cactus and vegetation indices obtained using UAVs are investigated, along with the prediction of these parameters utilizing machine learning algorithms. Four different experimental units were included in the study, analyzing plant height and width, vegetation indices, and fresh and dry yields. Higher correlations with yield were obtained for the RGBVI and ExGR indices, and predictive analysis using the Random Forest algorithm showed a mean absolute error of 1.39, 0.99 and 1.72 Mg ha^{-1} for the respective test units.

The fifth paper proposes a lightweight convolutional neural network (CNN), named LeafNet, for plant disease identification in resource-limited environments [12]. Inspired by the VGG19 architecture, LeafNet introduces a number of optimizations, including a reduced number of parameters and a fast inference time, while maintaining competitive accuracy. The study showed that LeafNet performs well in classification on four different datasets, including a newly completed plant collection, confirming its potential for use in real-world settings.

The advantages of integrating machine learning algorithms with Earth observation technologies, as the research presented here shows, have the potential to revolutionize approaches to crop management and plant health monitoring. These innovative methods have the potential to accelerate the response to changing environmental conditions and limitations associated with traditional agricultural methods. With the ability to rapidly process data and analyze images, these technologies allow for more effective disease detection, pest identification and yield assessment. The articles in this Special Issue demonstrate a variety of applications of machine learning algorithms, from applications in image classification, in the context of plant disease identification and diagnosis, to the use of dedicated frameworks for mobile pest detection or the complex analysis of biometric plant growth parameters using UAVs. Each of these studies highlights the importance of contemporary technologies in developing precise and efficient agricultural strategies that can significantly contribute to addressing the growing demand for food in an era of global climate change. In particular, research into the use of lightweight neural networks, such as LeafNet, shows that it is possible to achieve high accuracy in plant disease identification, even on devices with limited computing power [13,14]. This opens up new opportunities for farmers using mobile technologies, which is particularly relevant in the context of sustainable development. This Special Issue is a call for the further exploration and development of machine learning applications in agriculture. As the technology evolves, there is the potential to further optimize processes and strategies, resulting in more efficient and sustainable crop management. We encourage the research community to undertake further research in this area, which will not only improve the technology but also implement policy frameworks that foster innovation in agriculture, which is essential for future food security.

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