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Deep Learning-Based Crop Disease Detection for Precision Agriculture- A Survey

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Abstract: Crop diseases continue to pose a serious challenge to global agricultural productivity, leading to substantial yield losses, economic instability, and threats to food security. Conventional crop disease detection methods rely heavily on manual visual inspection by farmers or experts, which is time-consuming, subjective, and impractical for large-scale and continuous monitoring. In response to these limitations, recent advancements in precision agriculture have encouraged the adoption of intelligent and automated techniques for crop health assessment. This review paper critically examines a dissertation that presents a deep learning-based framework for crop disease detection using convolutional neural networks (CNNs). The reviewed study employs image-based analysis of crop leaf images and formulates the problem as a binary classification task, distinguishing between healthy and diseased crops. The proposed system integrates image preprocessing techniques with hierarchical feature extraction through CNN architectures, eliminating the need for handcrafted features. Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental findings demonstrate an overall classification accuracy of 93.75 percent, accompanied by balanced precision and recall values across both classes, indicating strong generalization and reliable disease detection capability. This review synthesizes the methodology, experimental outcomes, and significance of the study, while also highlighting existing limitations and potential directions for future research in intelligent precision agriculture systems.
Keywords: Crop Disease Detection, Deep Learning, Convolutional Neural Networks, Precision Agriculture, Image-Based Classification, Smart Farming.

I. INTRODUCTION

Agriculture forms the backbone of food security, economic stability, and rural livelihoods across the globe. A significant proportion of the world's population depends directly or indirectly on agricultural activities for sustenance and income generation. The productivity, profitability, and long-term sustainability of agricultural systems are closely associated with crop health, as healthy crops ensure optimal yield, better quality produce, and economic resilience for farming communities. However, agricultural production is persistently threatened by a wide range of crop diseases caused by fungi, bacteria, viruses, nematodes, and insect pests. These diseases adversely affect plant growth, physiological functions, and overall crop development, making them one of the leading contributors to yield reduction and post-harvest losses worldwide.Crop diseases not only reduce the quantity of agricultural output but also compromise the quality of produce, leading to lower market value and reduced consumer acceptance. In severe cases, disease outbreaks can result in partial or complete crop failure, causing substantial economic losses for farmers and threatening regional and global food security. The reviewed dissertation highlights that delayed detection of crop diseases significantly exacerbates these challenges. When diseases are not identified at an early stage, infections spread rapidly across cultivation areas, necessitating increased use of chemical pesticides.

Excessive pesticide application elevates production costs and poses serious environmental and health risks, including soil degradation, water contamination, biodiversity loss, and adverse effects on human health.Traditionally, crop disease identification has relied on manual visual inspection carried out by farmers or agricultural experts. Although such inspection-based methods benefit from experiential knowledge, they are inherently subjective, time-consuming, and inconsistent. Manual diagnosis becomes particularly impractical in large-scale farming environments where continuous monitoring of extensive fields is required. Moreover, early-stage disease symptoms are often subtle and visually similar across different diseases, making accurate identification difficult even for experienced practitioners. Environmental factors such as lighting conditions, humidity, soil fertility, and crop growth stages further complicate visual diagnosis. As a result, reliance on manual inspection frequently leads to misdiagnosis or delayed intervention, limiting its effectiveness in modern agriculture.In recent years, the concept of precision agriculture has emerged as a data-driven and technology-oriented approach to address the growing complexity of agricultural systems.

Precision agriculture focuses on optimizing crop management by monitoring spatial and temporal variability within fields and applying targeted interventions rather than uniform treatment. This paradigm aims to enhance productivity, reduce resource wastage, minimize environmental impact, and improve economic efficiency. Technologies such as remote sensing, digital imaging, Internet of Things (IoT) devices, and artificial intelligence play a central role in enabling precision agriculture practices. Within this context, automated crop disease detection has gained considerable attention due to its potential to support early diagnosis, timely decision-making, and sustainable disease management strategies.The reviewed dissertation positions automated crop disease detection as a critical component of precision agriculture. By analysing visual symptoms present on crop leaves, intelligent systems can assist farmers in identifying disease presence at an early stage, enabling prompt and targeted intervention. Among various artificial intelligence techniques, deep learning has emerged as a particularly powerful tool for image-based analysis. Deep learning models are capable of learning complex, non-linear patterns directly from raw data, making them well-suited for handling the variability and complexity inherent in agricultural images.

In particular, convolutional neural networks (CNNs) have demonstrated remarkable success in computer vision tasks such as image classification, object detection, and pattern recognition. The dissertation under review highlights CNNs as a transformative technology capable of overcoming the limitations of manual inspection and classical machine learning approaches. Unlike traditional methods that rely on handcrafted feature extraction, CNNs automatically learn hierarchical visual representations, capturing low-level features such as edges and color gradients as well as high-level disease-specific patterns such as lesions, discoloration, and texture irregularities. This ability enables CNN-based systems to achieve higher accuracy, better generalization, and greater robustness under diverse environmental conditions.Overall, the integration of deep learning-based crop disease detection within the precision agriculture framework represents a significant step toward intelligent, efficient, and scalable agricultural systems. By reducing dependence on manual inspection and enhancing early disease diagnosis, such approaches hold considerable promise for improving crop productivity, minimizing economic losses, and promoting sustainable farming practices.

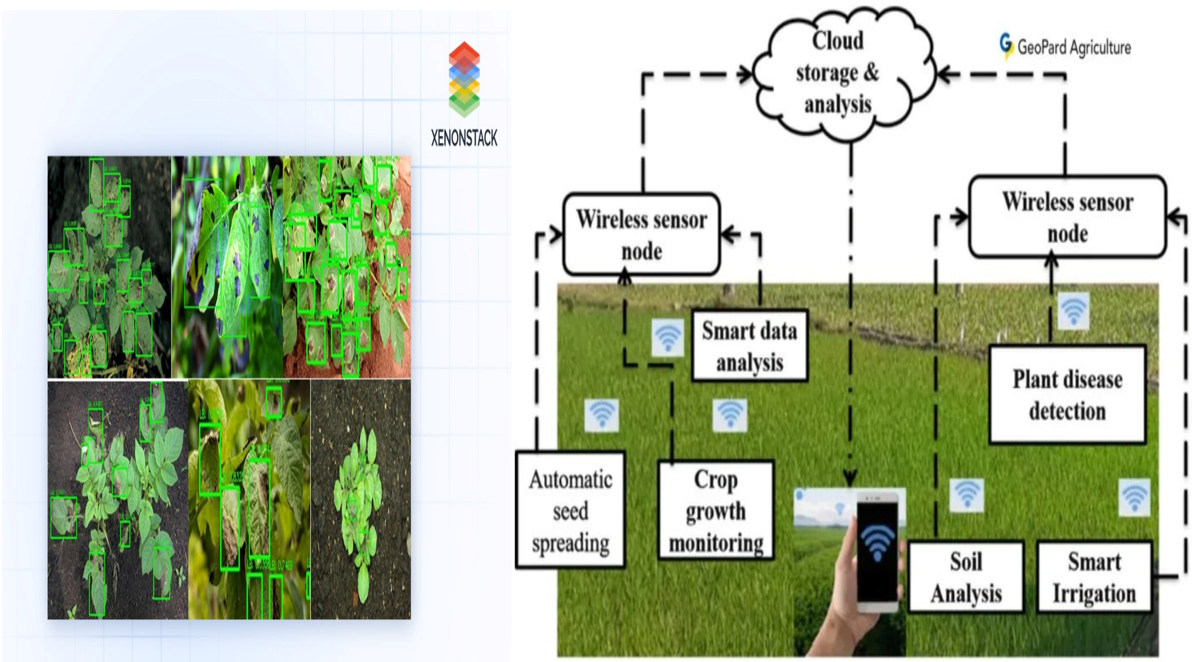

Figure 1: Applications of artificial intelligence and deep learning in precision agriculture for crop monitoring and disease detection.

II. EVOLUTION OF CROP DISEASE DETECTION TECHNIQUES

The evolution of crop disease detection techniques reflects the broader technological progression within agricultural research, moving from human-centered practices to automated and intelligent systems. In the early stages of agricultural development, disease identification was almost entirely dependent on traditional visual inspection performed by farmers and agricultural experts. Diagnosis was based on observing visible symptoms such as leaf discoloration, spots, wilting, lesions, and abnormal growth patterns. While this approach benefited from experiential knowledge accumulated over time, it was inherently subjective and inconsistent.

The accuracy of diagnosis depended heavily on individual expertise, environmental conditions, and the stage at which the disease was observed. As farming practices expanded in scale and complexity, the limitations of purely manual inspection became increasingly apparent, creating a strong need for technological assistance in crop disease identification.To address these challenges, early computational approaches to crop disease detection emerged, primarily based on classical image processing and conventional machine learning techniques. In these methods, digital images of crop leaves were analysed to extract handcrafted features that could represent disease-related characteristics. Commonly used features included color histograms to capture pigmentation variations caused by infection, texture descriptors to model surface irregularities, and shape-based features to identify deformities in leaf structure. Once these features were extracted, classification was typically performed using traditional machine learning algorithms such as support vector machines, k-nearest neighbors, decision trees, and naïve Bayes classifiers. Under controlled laboratory conditions with uniform lighting and simple backgrounds, these techniques achieved moderate levels of accuracy and demonstrated the feasibility of automated disease detection.However, the performance of classical image processing-based systems deteriorated significantly when applied to real-world agricultural environments. Agricultural images captured in the field are subject to wide variability due to fluctuating lighting conditions, complex and cluttered backgrounds, differences in camera quality, and variations in leaf orientation and growth stages. Handcrafted feature extraction methods are highly sensitive to such variations, often resulting in unstable or unreliable feature representations. Additionally, designing effective feature sets requires substantial domain expertise and careful parameter tuning, limiting scalability and adaptability. Feature sets optimized for one crop species or disease type often fail to generalize to others, necessitating repeated redesign and retraining. These limitations highlighted the inherent rigidity of traditional machine learning approaches and restricted their practical applicability in large-scale precision agriculture systems.

The reviewed dissertation emphasizes that the emergence of deep learning marked a fundamental paradigm shift in crop disease detection research. Deep learning techniques, particularly convolutional neural networks, introduced the ability to automatically learn discriminative features directly from raw image data. Unlike traditional methods, CNNs do not rely on manually engineered descriptors. Instead, they employ hierarchical representation learning, where multiple layers of convolution and pooling progressively extract increasingly abstract visual features. Initial layers typically learn low-level characteristics such as edges, contours, and color gradients, while deeper layers capture complex, high-level disease-specific patterns such as lesions, discoloration, and texture distortions.This hierarchical learning capability significantly enhances robustness and generalization across diverse datasets and environmental conditions. CNN-based systems demonstrate improved resilience to variations in lighting, background complexity, and image quality, which are common challenges in agricultural imaging. By eliminating the dependency on handcrafted features, deep learning-based approaches reduce subjectivity and improve scalability, making them more suitable for real-world deployment. As highlighted in the dissertation, this transition from traditional image processing to deep learning-based techniques represents a major advancement in automated crop disease detection, laying the foundation for intelligent and reliable precision agriculture systems.

III. DEEP LEARNING FOR IMAGE-BASED CROP DISEASE DETECTION

The reviewed dissertation adopts convolutional neural networks (CNNs) as the central analytical framework for image-based crop disease detection, reflecting current best practices in computer vision–driven agricultural research. CNNs are particularly well suited for analysing agricultural images because of their inherent ability to process spatial information and automatically learn hierarchical feature representations from raw pixel data. Unlike traditional image processing and machine learning approaches that rely on handcrafted features, CNNs learn discriminative visual patterns directly from data, enabling more accurate and robust disease detection under diverse conditions.According to the dissertation, crop diseases often manifest through subtle visual cues such as minor texture irregularities, early discoloration, small lesions, and abnormal surface patterns on leaves. These symptoms are frequently difficult to identify through manual inspection, especially during the early stages of infection. CNNs address this challenge by employing multiple convolutional layers that progressively learn increasingly abstract representations. Initial layers capture low-level features such as edges, contours, and color gradients, while deeper layers learn high-level disease-specific characteristics that distinguish healthy crops from diseased ones. This hierarchical learning mechanism allows CNNs to model complex visual variations inherent in agricultural imagery more effectively than classical methods.

The study further emphasizes the adaptability of CNN-based crop disease detection systems to real-world agricultural environments. Deep learning models demonstrate strong resilience to variations in lighting conditions, background clutter, leaf orientation, and image resolution, which are common challenges in field-acquired images. This robustness enhances generalization capability and supports reliable performance beyond controlled laboratory settings.

As highlighted in the dissertation, the automatic feature learning capability of CNNs eliminates the need for extensive domain expertise in feature design, thereby improving scalability and ease of deployment across different crops and farming regions.An important contribution of the reviewed work is its discussion of practical integration. CNN-based disease detection models can be deployed on mobile devices, unmanned aerial vehicles, and automated field monitoring platforms, enabling near real-time disease diagnosis. Such integration allows farmers to identify infections early and apply targeted interventions, reducing excessive pesticide usage and associated environmental risks. By supporting timely decision-making and sustainable disease management, deep learning-based image analysis emerges as a powerful and impactful tool for modern precision agriculture systems.

IV. DATASET DESIGN AND PREPROCESSING

A notable strength of the reviewed dissertation is its careful attention to dataset design and preprocessing, both of which play a critical role in the effectiveness of deep learning-based image analysis systems. The dataset employed in the study consists of 2000 crop leaf images, equally distributed between 1000 healthy and 1000 diseased samples. This balanced class distribution is particularly important for classification tasks, as it prevents model bias toward a dominant class and ensures that both healthy and diseased categories are learned with equal importance. In agricultural applications, where misclassification of diseased crops can have serious consequences, maintaining such balance is essential for achieving reliable and unbiased performance evaluation.The formulation of the problem as a binary classification task represents a pragmatic design choice. By focusing on distinguishing between healthy and diseased crops rather than identifying multiple disease types, the study simplifies the learning objective while retaining strong practical relevance. Early disease detection is often more critical than precise disease identification, as it enables timely intervention and prevents widespread infection. This binary framework supports early warning systems in precision agriculture, allowing farmers to take prompt action before diseases progress to more severe stages.

In addition to dataset composition, the dissertation places strong emphasis on image preprocessing as a foundational step in the proposed methodology. Raw agricultural images captured under field conditions often exhibit substantial variability due to changes in illumination, camera resolution, background complexity, and viewing angles. Such variability can introduce noise and inconsistencies that hinder effective feature learning. To address these challenges, all images in the dataset are resized to a uniform dimension, ensuring consistent input representation for the convolutional neural network. Uniform image sizing is crucial for CNNs, as it enables efficient batch processing and stable convolution and pooling operations during training.Furthermore, image normalization is applied to scale pixel intensity values within a predefined range. Normalization improves numerical stability during training by preventing large variations in pixel values from dominating gradient updates. This contributes to faster convergence and more stable learning behaviour. As emphasized in the dissertation, these preprocessing steps significantly reduce irrelevant variability and allow the CNN to focus on intrinsic disease-related visual patterns, such as texture irregularities, lesions, and discoloration. Overall, the dataset design and preprocessing strategy provide a robust foundation for effective learning, enhanced generalization capability, and reliable performance in real-world precision agriculture applications.

V. CNN ARCHITECTURE AND TRAINING STRATEGY

The proposed convolutional neural network architecture is carefully designed to achieve an effective balance between representational capacity and computational efficiency, making it suitable for crop disease detection in precision agriculture applications. Rather than relying on overly deep or complex networks, the model adopts a compact yet expressive structure that is capable of learning meaningful visual patterns while remaining feasible for deployment in resource-constrained environments. The architecture consists of two convolutional layers with 32 and 64 filters, respectively, which are responsible for hierarchical feature extraction from input crop leaf images. These layers enable the network to capture both low-level visual cues, such as edges and color variations, and higher-level disease-related patterns, including texture irregularities and lesions.Each convolutional layer is followed by a max-pooling operation, which reduces the spatial dimensions of the feature maps while preserving the most salient information.

Max-pooling contributes to computational efficiency by lowering the number of parameters and enhances the model’s ability to recognize disease patterns regardless of their spatial location on the leaf surface. After feature extraction, the resulting feature maps are flattened into a one-dimensional vector and passed to a fully connected dense layer comprising 128 neurons. This dense layer integrates the learned features and supports effective decision-making for classification. To improve generalization and reduce the risk of overfitting, dropout regularization is applied, followed by a sigmoid output layer suitable for binary classification.The training strategy further reinforces model robustness and stability. The network is trained using the Adam optimizer, which adaptively adjusts learning rates and promotes efficient convergence.

Binary cross-entropy is employed as the loss function, aligning well with the binary classification objective. Training is conducted with a batch size of 32 for 10 epochs, using a 20 percent validation split. The incorporation of dropout and early stopping helps mitigate overfitting, resulting in stable convergence and closely aligned training and validation accuracy and loss curves, indicating strong generalization capability.

VI. PERFORMANCE EVALUATION AND RESULTS

The performance evaluation of the proposed deep learning–based crop disease detection system demonstrates strong and reliable classification capability across both healthy and diseased categories. According to the dissertation, the model achieves an overall classification accuracy of 93.75 percent on the test dataset, indicating a high level of correctness in distinguishing between crop health conditions. While accuracy provides an overall measure of performance, the study appropriately employs additional evaluation metrics to gain deeper insight into class-wise behaviour and reliability, which is particularly important in agricultural applications where misclassification costs are unequal.For the healthy crop class, the model attains a precision of 0.9534, a recall of 0.9200, and an F1-score of 0.9364. The high precision value indicates that the majority of samples predicted as healthy are indeed healthy, reflecting a low false positive rate. The slightly lower recall suggests that a small number of healthy samples are misclassified as diseased, which represents a conservative classification tendency. For the diseased crop class, the model achieves a precision of 0.9227, a recall of 0.9550, and an F1-score of 0.9386. The high recall for diseased samples is particularly significant, as it indicates strong sensitivity to disease presence and reduces the risk of missing infected crops.Confusion matrix analysis further supports these findings, showing that 920 healthy samples and 955 diseased samples are correctly classified. Misclassifications primarily occur near class boundaries, where early-stage disease symptoms are visually subtle and difficult to distinguish. The model's tendency to favor disease detection is desirable in agricultural contexts, as minimizing false negatives helps prevent disease spread and supports timely intervention.

Table 1: Performance Metrics of the CNN-Based Crop Disease Detection Model

Class Label	Description	Precision	Recall	F1-Score	Correctly Classified Samples
Class 0	Healthy Crops	0.9534	0.9200	0.9364	920 / 1000
Class 1	Diseased Crops	0.9227	0.9550	0.9386	955 / 1000
Overall	—	—	—	—	Accuracy: 93.75%

VII. DISCUSSION AND CRITICAL ANALYSIS

The reviewed study convincingly demonstrates that deep learning-based crop disease detection provides a reliable and scalable alternative to traditional manual inspection and classical machine learning approaches. The reported overall classification accuracy of 93.75 percent, together with high recall values for diseased samples, confirms the effectiveness of convolutional neural networks in learning discriminative and disease-specific visual features from crop leaf images. High recall is particularly important in agricultural applications, as failure to detect diseased crops can result in rapid disease spread and significant yield loss. The balanced precision and recall values achieved across both classes further indicate that the proposed model does not exhibit class bias, enhancing its reliability for practical use.The dissertation appropriately recognizes that most misclassifications occur in visually ambiguous cases, particularly near the boundary between healthy and diseased classes. Such ambiguity is common in agricultural image analysis, especially during the early stages of disease development when symptoms are subtle and difficult to distinguish. Importantly, these errors are attributed to inherent visual similarities rather than deficiencies in the proposed model, underscoring the robustness of the learning framework. The conservative tendency of the model to favor disease detection is also noteworthy, as it aligns with practical agricultural priorities by minimizing false negatives.A notable strength of the reviewed work is its emphasis on computational efficiency alongside predictive performance. By adopting a relatively compact CNN architecture, the study enhances the feasibility of deployment in real-world precision agriculture environments, including resource-constrained settings. However, the analysis also highlights certain limitations. The model is restricted to binary classification and does not address multi-disease identification or severity estimation, which are important for precise treatment planning. Additionally, challenges related to real-world deployment, such as diverse field conditions, varying imaging devices, and environmental noise, remain outside the scope of the study and warrant further investigation.

VIII. CONCLUSION AND FUTURE DIRECTIONS

This review identifies the examined dissertation as a significant and timely contribution to the growing body of research on deep learning applications in precision agriculture. By systematically designing, implementing, and evaluating a convolutional neural network–based framework for crop disease detection, the study demonstrates how modern artificial intelligence techniques can effectively address long-standing challenges associated with traditional disease identification methods. The reported experimental results, including an overall classification accuracy of 93.75 percent with balanced precision and recall values across both healthy and diseased classes, confirm the robustness and reliability of the proposed approach. These findings validate the suitability of convolutional neural networks for image-based agricultural analysis and reinforce their potential for practical deployment in real-world farming environments.A key contribution of the reviewed work lies in its emphasis on balanced and efficient performance rather than solely maximizing accuracy. In agricultural contexts, misclassification costs are asymmetric, as failing to detect diseased crops can lead to rapid disease spread, severe yield losses, and increased economic burden for farmers. The demonstrated high recall for diseased samples indicates that the proposed system is particularly effective in identifying disease presence, which is essential for enabling early intervention and informed decision-making. Additionally, the relatively compact CNN architecture adopted in the study ensures computational efficiency, enhancing feasibility for deployment in resource-constrained agricultural settings where access to high-performance computing infrastructure may be limited.From a broader perspective, the dissertation underscores the transformative role of deep learning in advancing precision agriculture. By reducing reliance on manual visual inspection and minimizing subjectivity in diagnosis, automated crop disease detection systems can provide consistent and scalable support for crop health monitoring.

Such systems have the potential to empower farmers with timely and actionable insights, facilitating targeted disease management strategies that reduce excessive pesticide use, lower production costs, and mitigate environmental impact. In this regard, the reviewed study aligns closely with global efforts to promote sustainable and environmentally responsible farming practices while maintaining high levels of agricultural productivity.Despite its strengths, the dissertation also acknowledges certain limitations that present opportunities for future research. The proposed framework is limited to binary classification, distinguishing only between healthy and diseased crops. While this formulation is effective for early disease detection, it does not provide information about specific disease types or severity levels, which are often required for precise treatment decisions. Future research can extend this work by developing multi-class classification models capable of identifying a wider range of crop diseases and offering more detailed diagnostic insights.Another important direction for future research involves expanding dataset diversity and realism. Incorporating larger datasets collected under real field conditions, with variations in lighting, background complexity, crop species, and growth stages, would further enhance model generalization and robustness. Additionally, integrating the disease detection framework with real-time monitoring platforms, such as mobile applications, unmanned aerial vehicles, or Internet of Things–based agricultural systems, could enable continuous crop health surveillance and rapid response to emerging disease outbreaks.In conclusion, the reviewed dissertation confirms that deep learning-based crop disease detection represents a promising and impactful approach for enhancing agricultural productivity, sustainability, and food security. By providing a reliable foundation for intelligent crop health monitoring systems, the study offers valuable insights and a clear pathway for future advancements in precision agriculture.

REFERENCES

[1] Alippi, C., Roveri, M., &Santambrogio, M. (2018). Plant disease detection using deep learning techniques. IEEE Transactions on Industrial Informatics, 14(8), 3546–3555. https://doi.org/10.1109/TII.2018.2799445
[2] Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. Biosystems Engineering, 172, 84–91. https://doi.org/10.1016/j.biosystemseng.2018.05.013
[3] Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8), 1798–1828. https://doi.org/10.1109/TPAMI.2013.50
[4] Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer.
[5] Chaudhary, P., Chaudhari, A. K., Cheeran, A. N., &Godara, S. (2012). Colortransform based approach for disease spot detection on plant leaf. International Journal of Computer Science and Telecommunications, 3(6), 65–70.
[6] Esteva, A., Kuprel, B., Novoa, R. A., et al. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542, 115–118. https://doi.org/10.1038/nature21056
[7] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318. https://doi.org/10.1016/j.compag.2018.01.009
[8] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
[9] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770–778.

[10] Kamilaris, A., &Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

[11] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097–1105.

[12] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521, 436–444. https://doi.org/10.1038/nature14539

[13] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267, 378–384. https://doi.org/10.1016/j.neucom.2017.06.023

[14] Mohanty, S. P., Hughes, D. P., &Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419. https://doi.org/10.3389/fpls.2016.01419

[15] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification. Computers and Electronics in Agriculture, 161, 280–290. https://doi.org/10.1016/j.compag.2018.04.007

[16] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention, 234–241.

[17] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 2016, 1–11. https://doi.org/10.1155/2016/3289801

[18] Too, E. C., Yujian, L., Njuki, S., &Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture, 161, 272–279. https://doi.org/10.1016/j.compag.2018.03.032

[19] Zhang, S., Wu, X., & You, Z. (2017). Leaf image based cucumber disease recognition using sparse representation classification. Computers and Electronics in Agriculture, 134, 135–141. https://doi.org/10.1016/j.compag.2017.01.014

[20] Kamath, R., & Prasad, K. (2020). Precision agriculture using deep learning techniques: A review. Journal of Agricultural Informatics, 11(3), 1–15.

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