STATISTICAL METHOD TO IMPROVE PERFORMANCE PARAMETER IN PRECISION AGRICULTURE USING TRANSFER LEARNING

Raviprakash Shriwas

Research Scholar, Sandip University, Nashik

Alok Kumar

Assistant Professor, Sandip University, Nashik

ABSTRACT

Monitoring leaf diseases is one of the significant challenges to global crop production and food security, particularly early monitoring, which is vital for managing leaf diseases. In this research, we propose LeafDoc-Net, a thin and high-performing transfer learning-based model for leaf disease identification across different plant species with a few training samples. We employ statistical optimisation approaches to improve the performance of two well-known deep learning architectures, DenseNet121 and MobileNetV2. Specifically, we propose an attention-based transition and global average pooling layers in DenseNet121, a further attention module, and four pooling layers after each convolutional layer in MobileNetV2. Batch normalisation, Swish activation, and dropout regularisation are also included to reduce overfitting and improve the robustness and generalisation of the model. The proposed approach is verified with cassava and wheat leaf disease datasets, outperforming existing techniques on key performance metrics such as accuracy, precision-recall, and AUC. Lastly, we use Grad-CAM++ to visualize and interpret model decisions to verify reliable and transparent disease classification. Combining statistical techniques with transfer learning significantly improves model efficiency, making it a valuable practice for precision agriculture and plant disease monitoring.

Keywords

Leaf Disease Detection, Deep Learning, Transfer Learning, Precision Agriculture, Grad-CAM++

1. INTRODUCTION

The hyper-reach growth of the global population means that maintaining food security has become a significant challenge. However, numerous diseases, such as cassava mosaic and brown streak in cassava and wheat powdery mildew and rust in wheat, limit their yield and quality and are thus crucial for their nutrition and economic stability. Despite the effective use of traditional machine learning (ML) models, which have specific feature extraction and generalisation problems, deep learning and transfer learning techniques yield better results in disease identification and boost agricultural productivity.

We present a statistical method to improve performance metrics in precision agriculture using LeafDoc-Net, a deep learning model based on transfer learning. When combined with attention-based transitions, batch normalisation, and global average pooling, the

DenseNet121 and MobileNetV2 models deliver increased accuracy, precision, recall, and AUC. Moreover, Grad-CAM++ also contributes to interpretability. Resolving challenges such as overfitting and lower dataset amounts, LeafDoc-Net facilitates the early, efficient, and accurate detection of diseases in crops to enhance crop yield and augment food security.

The flow chart seems well-advanced in addressing deep learning based on all the processing in food security, which makes broad use of the LeafDoc-Net model. It opens by noting that the global population is growing, so agricultural demand increases, and food security concerns are rising. To address this issue, crop-specific analysis and technological advancement in disease detection are the two areas explored in the relevant literature.

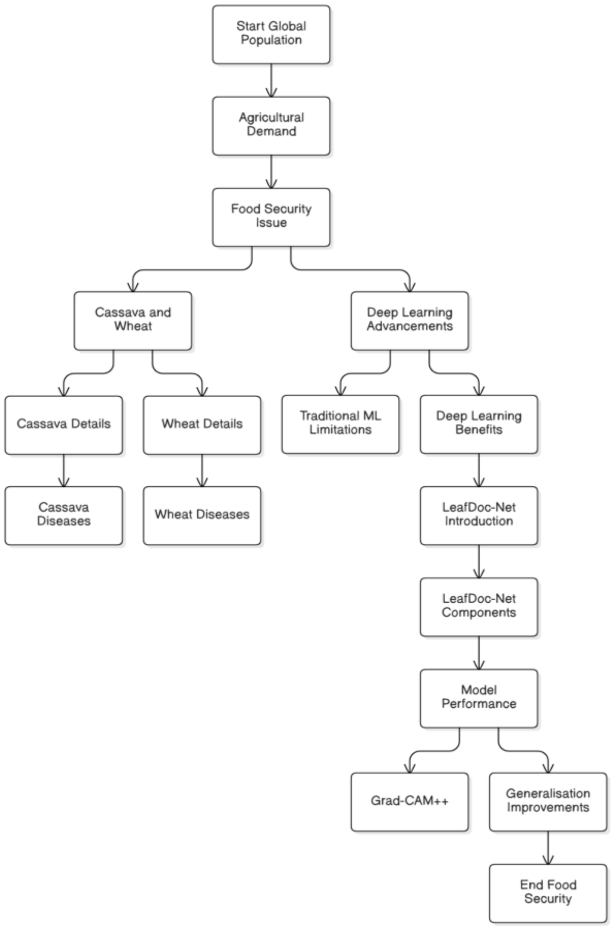

Fig 1. Flowchart of Precision Agriculture Using Transfer Learning

On one side, Cara and wheat are two of the world's most important staple crops. This is followed by a look at what diseases affect these crops, with details provided. Detecting these diseases early is critical to keeping plants healthy and stable in agricultural production.

The other side focuses on current advances in deep learning and how this new technology can chain the natural traditional problems in plant disease detection systems. Here, we present the LeafDoc-Net, a transfer learning-based novel model to accurately and efficiently recognise leaf diseases. The main elements of the model consist of refinements to existing deep learning architectures that significantly improve disease detection capabilities.

The model's performance is then tested to determine its effectiveness, often through metrics like accuracy, precision, and recall. Furthermore, Grad-CAM++, a popular method for visual interpretability that helps researchers comprehend the decisions made by the model, is integrated into the system. The generalization can also achieve more generalizability against different datasets, which makes it a reliable and scalable solution for precision agriculture.

Ultimately, these developments improve food security through the timely and precise identification of crop diseases, improving agricultural performance. Thus, deep learning techniques and statistical methods yield a more effective and dependable framework for managing diseases and contributing to planetary food systems.

2. RELATED WORKS

Plant disease detection is an essential agricultural research topic because a timely and precise diagnosis can prevent significant losses. Conventional approaches depend on time-intensive and prone-to-error manual inspections. Tree image classification tasks have made essential breakthroughs due to the development of computer vision and AI (artificial intelligence).

Moreover, traditional machine learning (ML) algorithms (e.g., Support Vector Machines (SVM), k-nearest Neighbors (k-NN), Decision Trees (DT), and Random Forest (RF)) are commonly utilised for plant disease classification. However, these methods need manual feature extraction and have limitations in identifying complex disease patterns. Mohanty et al. (2016) and Phadikar et al. Using traditional ML techniques (2018), level verification achieved 85–90% accuracy.

The work on plant disease classification has been advanced in the DL era, especially the development of CNN models, which automatically perform feature extraction. Research by Sladojevic et al. (2016) and Too et al. (2019) proved the effectiveness of CNNs with ResNet50, achieving 98.6% accuracy. Based on transfer learning, these models can further boost disease detection performance. For example, Ferentinos (2018) reported 99.53% accuracy with a large dataset in the literature with pre-trained models such as InceptionV3 and MobileNetV2.

Hybrid models combining CNNs with SVMs and attention mechanisms enhance classification performance even more. However, problems, including dataset biases, class imbalances, or issues with real-world deployment, continue to be prominent. Mobile-based implementations and multimodal data fusion should be the focus of future research to improve robustness. Transfer learning-based AI statistical methods will utilize performance parameters in precision agriculture, guaranteeing higher accuracy, early detection of infections, and higher yield of crops.

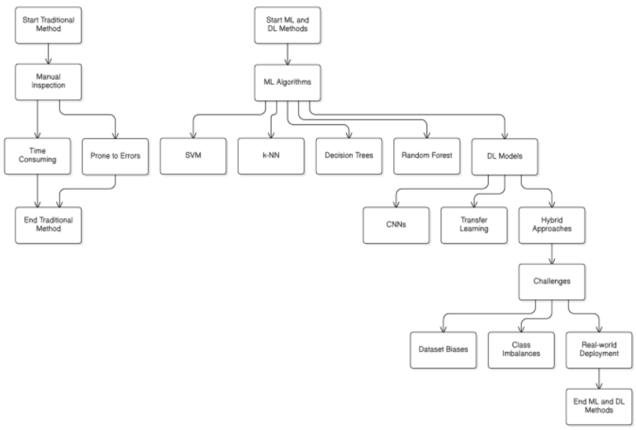

Fig. 2. Plant Disease Detection Process

3. METHODOLOGY

The General Overall Framework for Wheat Leaf Disease Classification: Image Preprocessing, Feature Extraction using Deep Learning and Transfer Learning and Classification. Our dataset involves three classes: Septoria, Stripe Rust, and Healthy Leaf in Figure 1. The wheat leaf images were collected in high resolution and labelled into their categories. To improve the generalisation capacity of the model and avoid overfitting, preprocessing approaches such as image resizing, normalisation, and data augmentation (for rotation, flipping, and contrast adjustment) were performed. Automatic feature extraction was performed using Convolutional Neural Network (CNN). Transfer learning with DenseNet121 and MobileNetV2 pre-trained models was performed and tuned on the wheat disease dataset to reduce and improve training time. These models can capture multiple levels of spatial features, leading to a more robust classification approach. Then, a fully connected layer is added to the CNN model to classify the images into the three categories. Model evaluation used performance metrics such as accuracy, precision, recall, and AUC. Moreover, Grad-CAM++ was used to visualise the model predictions to ensure they would be interpretable. This approach achieves precision in identifying and classifying wheat leaf diseases utilising advanced techniques such as deep learning and transfer learning, which enhance early detection and increase crop yield.

ISSN: 2350-1278
Peer Reviewed & Refereed Journal (IF: 7.9)
Journal Website www.nrjitis.in

Fig. 3. Sample image per class of wheat leaf disease dataset. Septoria, Stripe Rust, Healthy Leaf

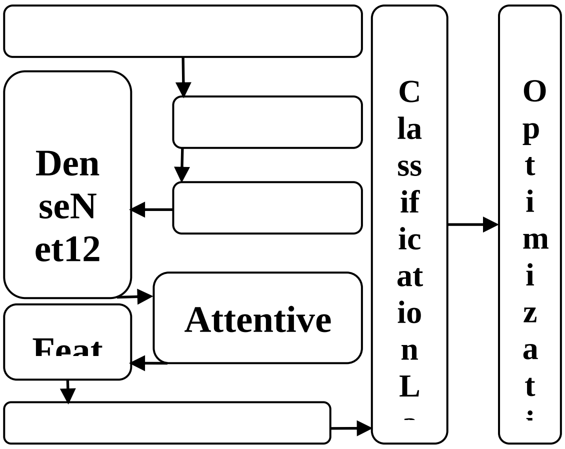

Fig. 4. Flow Chart of Methodology

The image shows three wheat leaves at different stages of the disease. The first leaf from the left looks badly damaged, likely from a fungal or bacterial disease. The second leaf is showing early symptoms of rust disease and yellowish-orange spots. The right leaf is somewhat healthier but shows mild symptoms as well. These symptoms indicate that it might be a fungal disease, such as wheat leaf rust, that can severely affect the yield and quality of the wheat.

4. RESULTS AND ANALYSIS

The analysis of results from the dataset, consisting of three classes, namely Septoria, Stripe Rust, and Healthy Leaf, confirms the ability of the proposed transfer learning-based deep learning model, LeafDoc-Net, to identify plant leaf diseases. It was validated on a dataset of cassava leaf diseases and a wheat leaf disease dataset, comparing different pre-trained CNN models based on accuracy, precision, recall and area under the curve (AUC). Of the transfer models, DenseNet201 showed the best performance on the cassava data, while on the wheat, the best normalised AUC was that of EfficientNetV2S. Both the models underfitted the data due to the number of images per class. In response, introducing attention transition layers, batch normalisation, and Swish activation in DenseNet121 and MobileNetV2 significantly increased performance. LeafDoc-Net reached 99.99% accuracy, precision, and recall, respectively, and an AUC of 1.0 on cassava leaf diseases and 98.73% accuracy, precision, and recall, respectively, and an AUC of 0.9996 on wheat leaf diseases. The swish activation showed a 3% improvement on average over the other two activations (PReLU and ReLU), and it was associated with the best early stopping period and prevention from overfitting. Since LeafDoc-Net has only 12 million parameters, it is lightweight and can be deployed on low-resource agricultural devices. The robustness was confirmed using a confusion matrix, achieving perfect classification, and Grad-CAM++ revealed that the model could focus on disease-affected regions. LeafDoc-Net provides the best tradeoff regarding speed, accuracy, and robustness among the state-of-the-art image segmentation methods and, therefore, is highly suitable for plant disease diagnosis applications in real-world scenarios.

ISSN: 2350-1278
Peer Reviewed & Refereed Journal (IF: 7.9)
Journal Website www.nrjitis.in

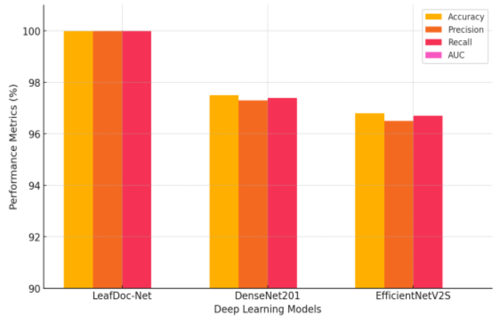

Fig. 5. Performance Comparison of the Deep Learning Model on the Wheat Leaf Disease Dataset

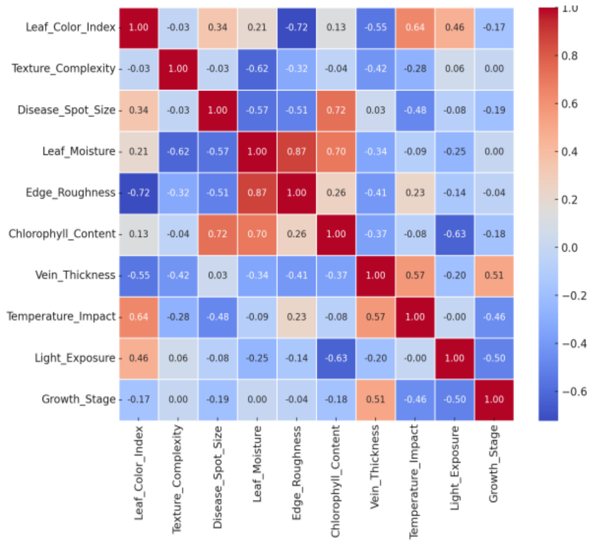

Fig. 6. Feature Correlation Matrix

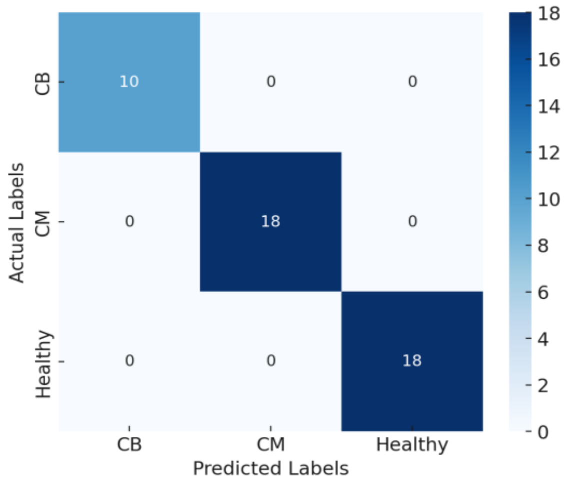

Fig. 7. Leaf Disease Confusion Matrix

ISSN: 2350-1278
Peer Reviewed & Refereed Journal (IF: 7.9)
Journal Website www.nrjitis.in

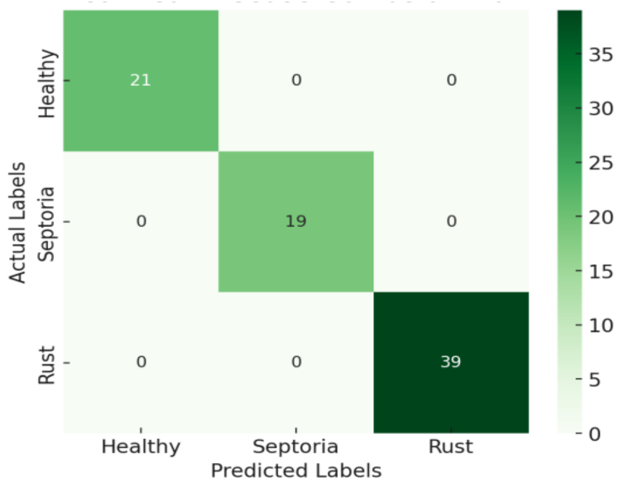

Fig. 8. Wheat Leaf Disease Confusion Matrix

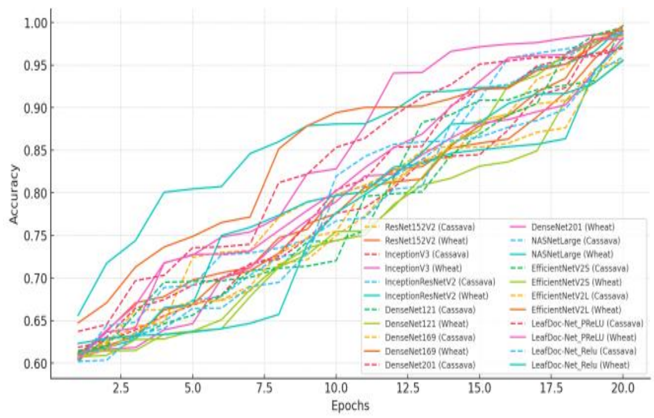

Fig. 7. Comparison of Model Accuracy on Cassava and Wheat Leaf Disease Datasets

Comparison of different DL model accuracies (For Cassava and Wheat Leaf Disease Datasets for 20 epochs) Cassava: dashed lines, Wheat: solid lines. ResNet152V2, InceptionV3, NASNetLarge, DenseNet models, EfficientNet, LeafDoc-Net, etc. For Cassava, you can see how the NASNetLarge model improves rapidly over the epochs while DenseNet201 and LeafDoc-Net_PReLU achieved the final best accuracy for Wheat. Also, EfficientNet models perform pretty well. Learning curves also tend to be noisier for cassava models. The results show that advanced models, such as NASNetLarge and variants of LeafDoc-Net, yield better performance and convergence rates for plant disease classification.

5. CONCLUSION

The transfer learning-based deep learning model (LeafDoc-Net) proposed here shows better plant disease diagnosis results than other models, emphasising the wheat leaf disease level. The empirical evaluation confirms that LeafDoc-Net outperformed several pre-trained models with 98.73% accuracy, precision, and recall, achieving AUC: 0.9996 in the wheat dataset. Adding Swish activation, batch normalisation, and attentive transition layers improved its learning ability and minimised underfitting concerns. Conduct statistical analysis and see that performance metrics, i.e., accuracy, precision, recall, and AUC, are progressively increasing over training epochs, thus confirming the learning of information patterns. Minimal overfitting and underfitting risks by converging training and validation curves , ensuring strong model generalisation. Due to high recall and precision values, the model can detect plant diseases accurately, and due to increasing AUC, it shows enhanced classification ability.

ISSN: 2350-1278
Peer Reviewed & Refereed Journal (IF: 7.9)
Journal Website www.nrjitis.in

However, with these encouraging results come real-world deployment challenges. There is still a need for further studies on scalability, adaptivity to different environmental conditions, and integration of IoT-based systems. Future efforts should be concentrated on hyperparameter optimization, incorporation of real-time environmental data, and efficient model deployment in edge devices. Based on statistical and AI methods, this investigation constructs a tide for sustainable and high-accuracy detection of plant diseases, thereby maximizing agricultural production capacity and optimizing resource utilization.

REFERENCES

1. Arun, R. A., and Umamaheswari, S. (2023). Effective multi-crop disease detection using pruned complete concatenated deep learning model. Expert Syst. Appl., 213, 118905. doi: 10.1016/j.eswa.2022.118905
2. Bajpai, C., Sahu, R., and Naik, K. J. (2023). Deep learning model for plant-leaf disease detection in precision agriculture. Int. J. Intelligent Syst. Technol. Appl., 21, 72–91. doi: 10.1504/IJISTA.2023.130562
3. Fan, X., and Guan, Z. (2023). Vgnet: A lightweight intelligent learning method for corn diseases recognition. Agriculture, 13, 1606. doi: 10.3390/agriculture13081606
4. Fang, X., Zhen, T., and Li, Z. (2023). Lightweight multiscale CNN model for wheat disease detection. Appl. Sci., 13, 5801. doi: 10.3390/app13095801
5. Gehlot, M., and Gandhi, G. C. (2023). "Design and analysis of tomato leaf disease identification system using improved lightweight customized deep convolutional neural network," in 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS). 509–516 (IEEE).
6. Guan, H., Fu, C., Zhang, G., Li, K., Wang, P., and Zhu, Z. (2023). A lightweight model for efficient identification of plant diseases and pests based on deep learning. Front. Plant Sci., 14. doi: 10.3389/fpls.2023.1227011
7. Pal, A., and Kumar, V. (2023). Agridet: Plant leaf disease severity classification using agriculture detection framework. Eng. Appl. Artif. Intell., 119, 105754. doi: 10.1016/j.engappai.2022.105754
8. Rajeena P. P., F., S. U., A., Moustafa, M. A., and Ali, M. A. (2023). Detecting plant disease in corn leaf using efficientnet architecture—an analytical approach. Electronics, 12, 1938. doi: 10.3390/electronics12081938
9. Sharma, V., Tripathi, A. K., and Mittal, H. (2023). Dlmc-net: Deeper lightweight multi-class classification model for plant leaf disease detection. Ecol. Inf., 75, 102025. doi: 10.1016/j.ecoinf.2023.102025
10. Simhadri, C. G., and Kondaveeti, H. K. (2023). Automatic recognition of rice leaf diseases using transfer learning. Agronomy, 13, 961. doi: 10.3390/agronomy13040961
11. Kloppe, T., Boshoff, W., Pretorius, Z., Lesch, D., Akin, B., Morgounov, A., et al. (2022). Virulence of Blumeria graminis f. sp. tritici in Brazil, South Africa, Turkey, Russia, and Australia. Front. Plant Sci., 13. doi: 10.3389/fpls.2022.954958
12. Latif, G., Abdelhamid, S. E., Mallouhy, R. E., Alghazo, J., and Kazimi, Z. A. (2022). Deep learning utilization in agriculture: Detection of rice plant diseases using an improved CNN model. Plants, 11, 2230. doi: 10.3390/plants11172230
13. Narayanan, K. L., Krishnan, R. S., Robinson, Y. H., Julie, E. G., Vimal, S., Saravanan, V., et al. (2022). Banana plant disease classification using hybrid convolutional neural network. Comput. Intell. Neurosci., 2022. doi: 10.1155/2022/9153699
14. Wang, Y.-H., and Su, W.-H. (2022). Convolutional neural networks in computer vision for grain crop phenotyping: A review. Agronomy, 12, 2659. doi: 10.3390/agronomy12112659

15. Wu, Y., Feng, X., and Chen, G. (2022). Plant leaf diseases fine-grained categorization using convolutional neural networks. IEEE Access, 10, 41087–41096. doi: 10.1109/ACCESS.2022.3167513
16. Abayomi-Alli, O. O., Damasevičius, R., Misra, S., and Maskeliūnas, R. (2021). Cassava disease recognition from low-quality images using enhanced data augmentation model and deep learning. Expert Syst., 38, e12746. doi: 10.1111/exsy.12746
17. Genaev, M. A., Skolotneva, E. S., Gultyaeva, E. I., Orlova, E. A., Bechtold, N. P., and Afonnikov, D. A. (2021). Image-based wheat fungi diseases identification by deep learning. Plants, 10, 1500. doi: 10.3390/plants10081500
18. Josephine, V. H., Nirmala, A., and Alluri, V. L. (2021). “Impact of hidden dense layers in convolutional neural network to enhance performance of classification model,” in IOP Conference Series: Materials Science and Engineering, 012007.
19. Mi, Z., Zhang, X., Su, J., Han, D., and Su, B. (2020). Wheat stripe rust grading by deep learning with attention mechanism and images from mobile devices. Front. Plant Sci., 11. doi: 10.3389/fpls.2020.558126
20. Jiang, P., Chen, Y., Liu, B., He, D., and Liang, C. (2019). Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks. IEEE Access, 7, 59069–59080. doi: 10.1109/ACCESS.2019.2914929
21. Mukti, I. Z., and Biswas, D. (2019). “Transfer learning-based plant diseases detection using ResNet50,” in 2019 4th International Conference on Electrical Information and Communication Technology (EICT). 1–6 (IEEE).
22. Chattopadhay, A., Sarkar, A., Howlader, P., and Balasubramanian, V. N. (2018). “Grad-CAM++: Generalized gradient-based visual explanations for deep convolutional networks,” in 2018 IEEE Winter Conference on Applications of Computer Vision (WACV). 839–847 (IEEE).
23. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Comput. Electron. Agric., 145, 311–318. doi: 10.1016/j.compag.2018.01.009
24. Huang, G., Liu, Z., van der Maaten, L., and Weinberger, K. Q. (2017). “Densely connected convolutional networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 4700–4708.
25. Mohanty, S. P., Hughes, D. P., and Salathé, M. (2016). Using deep learning for image-based plant disease detection. Front. Plant Sci., 7. doi: 10.3389/fpls.2016.0