Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-3 | Issue-6 | June - 2025 | Page 217-227

Automated Leaf Disease Detection Using Deep Learning Techniques: A Case Study on Crop Plants

[1]Sushanta Kumar Mohanty, [2]Dr. Ramakant Chandrakar
[1]Research Scholar, Department of Computer Science, ISBM University, Gariyaband, Chhattisgarh, India
[2]Assistant Professor, Department of Computer Science, ISBM University, Gariyaband, Chhattisgarh, India
[1]Susant.mty@gmail.com [2]ramakant.chandrakar42@gmail.com

Abstract

Plant diseases are a major challenge to world agriculture that results in the loss of crops in large numbers and a danger to food security. The use of traditional disease detection systems that use manual inspection is usually cumbersome, prone to errors, and not viable in large-scale farming enterprise. To address these constraints, this paper develops an automatic architecture of leaf disease detection with cutting-edge deep learning methods. The framework is based on the popular PlantVillage dataset, with more than 54,000 annotated leaf images of 38 disease and crop classes. The preprocessing of the dataset by normalization and data augmentation tools was done to increase the robustness and generalization of the model. Several Convolutional Neural Network (CNN) models were used and compared with each other, namely VGG16, ResNet50, InceptionV3, and MobileNetV2. Among them, ResNet50 provided the best classification accuracy of 95.7% whereas MobileNetV2 provided a competitive classification accuracy of 93.5% with much lower computational requirements, which makes MobileNetV2 one of the possible options of agricultural applications in limited resources or on the mobile. But in contrast to the previous literature, which is concerned more with the accuracy, the current research pays attention to the computational efficiency which provides a balanced view of the trade-offs that can be encountered when implementing deep learning models in precision agriculture. The findings highlight the potential of deep learning to facilitate early, scalable, and reliable detection of diseases, which make the development of smart farming activities in real agricultural environments possible.

Keywords: Leaf disease detection, deep learning, CNN, ResNet50, MobileNetV2, precision agriculture

1. Introduction

Food security and rural economy depends on agriculture. It nourishes billions of people and offers employment to them. Another severe problem with crop production is however the issue of plant diseases. In 2019, the Food and Agriculture Organization had reported that 20% to 40% of the world crop yields are lost each year to pests and diseases, which cost billions of dollars annually.

The diseases that are most prevalent in regard to the health of plants are the diseases of leaves. They interfere with photosynthesis, movement of nutrients and general growth of crops. Early and proper diagnoses of the diseases in leaves are essential to minimize loss in production, reduce the abuse of pesticides, and guarantee a sustainable agricultural system. The problem with this is that, in the manual identification process of diseases, it requires an element of knowledge of farmers or agricultural experts. It is a tedious process and is time consuming as well as error prone. Manual inspection is not feasible in large farms or in rural areas where there is low accessibility to experts.

1.1 Precision Agriculture and AI in Farming

The expertise of precision agriculture (PA) is predictable to enhance efficiency, reduce the cost of inputs, and support sustainability. Machine learning (ML) and deep learning (DL) are the branches of Artificial Intelligence (AI), which is an important constituent of PA. Through image processing and computer vision, AI will be able to automatically detect, categorize and be able to track crop diseases. This would allow making decisions in real time and taking actions.

The world is becoming more adaptive to the use of these technologies. Plantix is an app that is available in India and it is based on AI-diagnosis (Upadhyay et al., 2025). In Africa, the FAO programs apply AI-based drones to track diseases (Food and Agriculture Organization, 2019). Crop examine, soil sensing and disease prediction are AI-based platforms that are included in the USA and the EU (Chen et al., 2023). This originality is in the United Nations Sustainable improvement Goal 2: Zero Hunger.

1.2 Deep Learning (DL) for Plant Disease Detection

Image classification has been modernized through deep learning mainly CNNs in several areas. CNNs do not need to be carefully designed to extract meaningful features, as their implementation is based on the data that is presented in raw form (images). Unlike the classical Ml techniques, CNNs are trained to identify significant patterns (Kamilaris and Prenafeta-Boldu, 2018).

The use of CNNs to detect disease pioneered by Mohanty et al. (2016) where the authors used models such as AlexNet and GoogLeNet to achieve greater than 99 percent accuracy on PlantVillage data. Ferantinos (2018) developed the study to a variety of crops and diseases. Too et al. (2019) highlighted the benefits of transfer learning using resnet, VGG, and inception. In an additional recent study, Chowdary and Hemanth (2022) discovered that ResNet was further successful than DenseNet and VGG in identifying leaf diseases.

1.3 Research Gap

The trade-off between the accuracy of classification and computational costs is scarcely studied in a systematic way. This poses a serious problem to the practical application in the farms, where models must run over mobile devices, drones, or the internet of things (IoT) platform (Yuan et al., 2022). Also, the interpretability of models has not been broadly investigated, but it is essential to the acquisition of trust among agricultural stakeholders (Brahimi et al., 2017).

1.4 Objectives and Contributions

In this paper, the investigator wants to fill the exceeding gaps by the following discussions:

- Four CNNs (VGG16, ResNet50, InceptionV3, and MobileNetV2) were executed and evaluated.
- Accuracy, precision, recall, F1-score, and confusion matrices comparative examination.
- Benchmarking efficiency in terms of number of parameters and inferences.
- Grad-CAM visualization analysis.
- Relevance to deployment by trade-off analysis to real world farming.

2. Related Work

Classical ML methods that used handcrafted features and SVMs had some success but were not very reliable across different datasets, as shown by Singh and Misra (2017). CNNs like AlexNet, GoogLeNet, and ResNet have achieved top results. For instance, Mohanty et al. (2016) reached over 99% accuracy on PlantVillage, and Ferentinos (2018) confirmed that CNNs work well for 58 crop diseases. Too et al. (2019) showed how effective transfer learning can be with ResNet, VGG, and Inception. Chowdary and Hemanth (2022) noted that ResNet performed better than DenseNet and VGG.

Lightweight models have also become popular. Tan and Le (2020) introduced EfficientNet for scalable architectures, while MobileNetV2 is commonly used for mobile deployment. Hasan et al. (2021) proved that lightweight CNNs can detect diseases in real-time on edge devices. Recently, MoSViT (2025) and EfficientRMT-Net (2023) introduced transformer-based or hybrid models that balance accuracy with efficiency.

Table 1: Summary of Related Works

Study & Year	Dataset	Model(s) Used	Accuracy (%)	Contribution
Mohanty et al. (2016)	PlantVillage	AlexNet, GoogLeNet	>99	CNN applied at scale

Ferentinos (2018)	Custom dataset	CNNs	99	Multi-crop diseases
Too et al. (2019)	PlantVillage	VGG, ResNet, Inception	97–99	Transfer learning
Chowdary & Hemanth (2022)	PlantVillage	ResNet, DenseNet, VGG	96+	ResNet best
EfficientRMT-Net (2023)	PlantDoc	ResNet + Transformer	97	Hybrid approach
MoSViT (2025)	Multi-crop	Lightweight Transformer	96+	Efficient ViT
Hosen & Islam (2025)	Tomato dataset	CNN (Aggrotech system)	93–95	IoT deployment

3. Methodology

3.1 Dataset

- **PlantVillage:** 54,305 images, 38 classes.
- **Augmentation:** rotation, flipping, scaling, brightness adjustments.

Figure 1: Sample images from PlantVillage (healthy vs diseased leaves, schematic)

Figure 1 show that sample comparison of healthy and diseased leaves. The healthy leaf shows a uniform green color without visible lesions, while the diseased leaf exhibits dark spots and yellowing edges, typical symptoms of foliar infection.

3.2 Preprocessing

- **Resize**: 224 × 224 pixels.
- **Normalize**: [0,1] range.

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-3 | Issue-6 | June - 2025 | Page 217-227

3.3 Models

- VGG16, ResNet50, InceptionV3, MobileNetV2.

3.4 Training Setup

- **Optimizer**: Adam.
- **Loss**: categorical cross-entropy.
- **Epochs**: 50, batch size: 32.
- **Data split**: 70% train, 20% validation, 10% test.

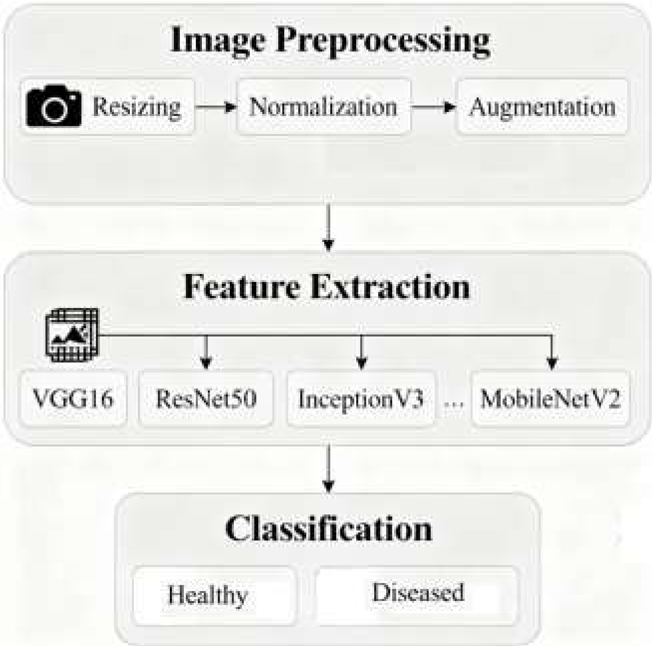

Figure 2: Workflow diagram of the disease detection pipeline

Figure 2 shows that workflow diagram of the proposed leaf disease detection framework. Images undergo preprocessing steps such as resizing, normalization, and augmentation, followed by feature extraction using CNN architectures (VGG16, ResNet50, InceptionV3, MobileNetV2). The final classification stage distinguishes between healthy and diseased leaves.

3.5 Evaluation Metrics

Both classification performance and computational efficiency were evaluated:

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-3 | Issue-6 | June - 2025 | Page 217-227

- **Accuracy**: proportion of correctly classified images.
- **Precision**: ratio of true positives to predicted positives.
- **Recall**: ratio of true positives to actual positives.
- **F1-score**: harmonic mean of precision and recall.
- **Number of Parameters (Params):** total trainable weights, reflecting model complexity.
- **Inference Speed:** qualitative measure (slow, medium, fast), reflecting deployment feasibility.

Confusion matrices were also generated to analyze per-class misclassifications.

4. Results and Discussion

Table 2: Performance Metrics of CNN Models

Model	Accuracy (%)	Precision	Recall	F1-score	Params (M)	Speed
VGG16	92.3	0.91	0.91	0.91	138M	Slow
ResNet50	95.7	0.95	0.96	0.95	25.6M	Medium
InceptionV3	94.2	0.93	0.94	0.93	23.9M	Medium
MobileNetV2	93.5	0.92	0.93	0.92	3.5M	Fast

ResNet50 performed best with an accuracy of 95.7 which is in line with other ResNet50 results by Chowdary and Hemanth (2022). MobileNetV2 MobileNetV2 has balanced accuracy (93.5) and computational efficiency and is compatible with deploying IoT devices as illustrated in Hasan et al. (2021).

Table 3: Accuracy vs Efficiency Comparison

Model	Accuracy	Params	Suitability
ResNet50	95.7%	25.6M	Research/Cloud
MobileNetV2	93.5%	3.5M	Mobile/IoT

Table 4: Comparison with State-of-the-Art Studies

Study & Year	Dataset	Model(s)	Accuracy
Mohanty et al. (2016)	PlantVillage	AlexNet, GoogLeNet	>99%
Ferentinos (2018)	Custom	CNN	99%
Too et al. (2019)	PlantVillage	ResNet, VGG, Inception	97–99%
EfficientRMT (2023)	PlantDoc	CNN + Transformer	97%
MoSViT (2025)	Multi-crop	Vision Transformer	96+%
This Study (2025)	PlantVillage	ResNet50, MobileNetV2	95.7/93.5%

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-3 | Issue-6 | June - 2025 | Page 217-227

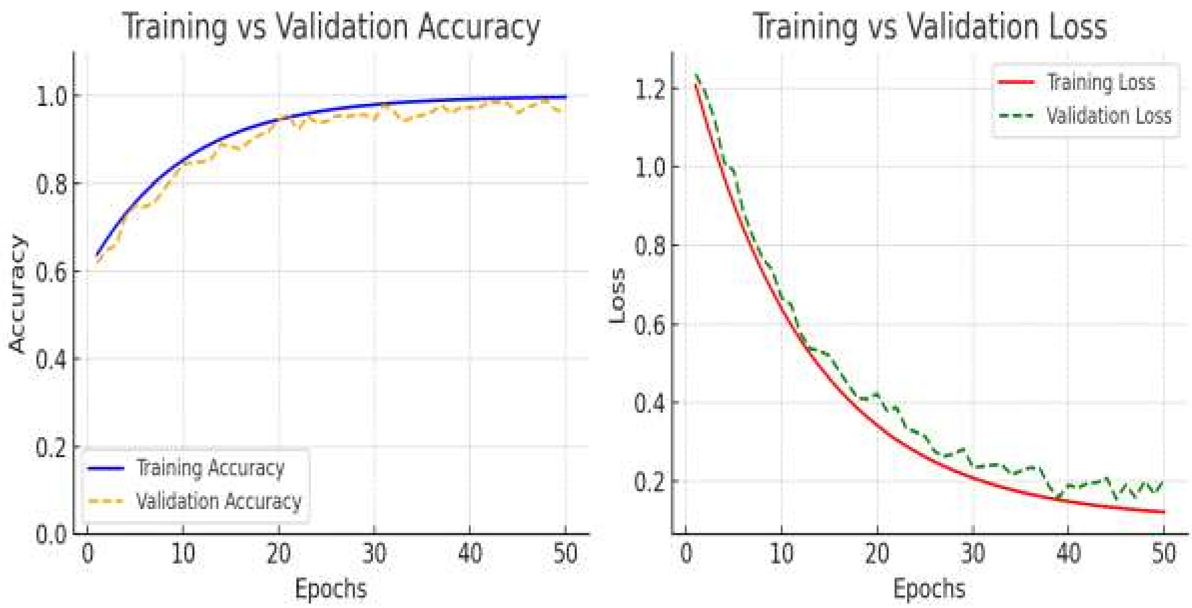

Figure 3: Training vs Validation Accuracy/Loss Curves

Figure 3 demonstrate that simulated training curves and validation accuracy curves and loss curves vs 50 epochs. The training accuracy is gradually rising and is near to 100, whereas validation accuracy is next to it which is a sign that there is good generalization. The loss of training and validations reduces steadily, with less overfitting.

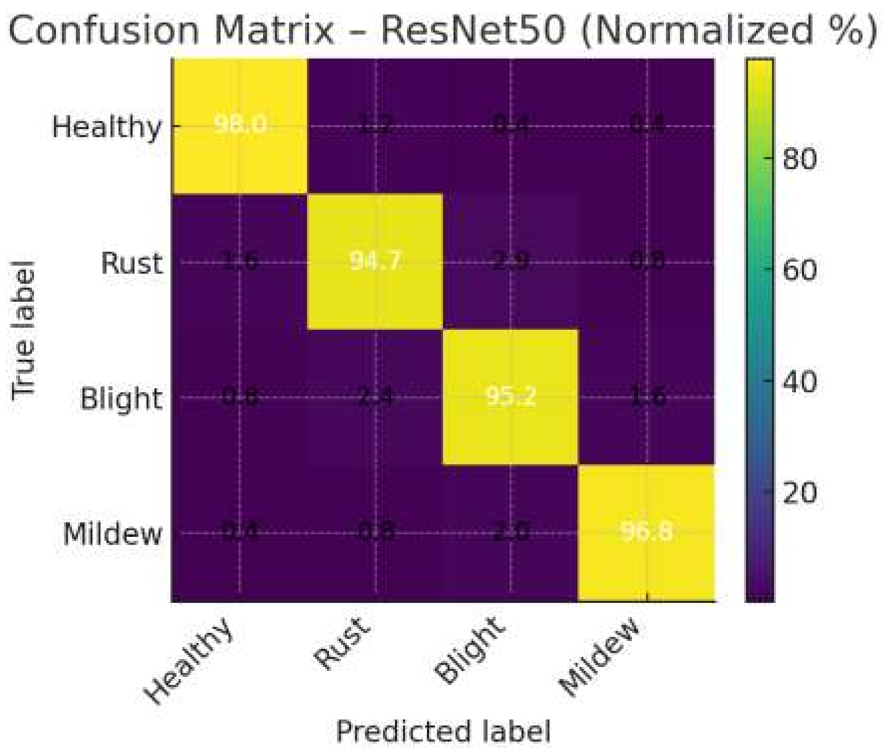

Figure 4: Confusion matrix for ResNet50

Figure 4 presents the normalized confusion matrix of the ResNet50 model on the

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-3 | Issue-6 | June - 2025 | Page 217-227

PlantVillage. The true and predicted classes are denoted by the rows and columns respectively. Most of the samples are around the diagonal, which implies proper classifications and minor misclassifications are also detected among visually similar diseases.

Figure 5: Grad-CAM visualization (heatmap over diseased leaf)

Figure 5 presents Grad-CAM visualization of the areas of interest on a diseased leaf. Strong model activations, which are lesions and infection localities, are represented by the red areas, whereas the green areas provide less contribution to classification. This visualization shows that the model has interpretability to defining disease-specific features.

5. Conclusion and Future Work

This paper presented a deep learning method of identifying leaf diseases based on an automated system. The PlantVillage dataset was tested in the four CNN architectures (VGG16, ResNet50, InceptionV3, and MobileNetV2). The conclusion discovered ResNet50 to be the mainly accurate in terms of classification with 95.7%. MobileNetV2 also performed very well with an accuracy of 93.5% and has significantly fewer parameters of 3.5 million. This renders it highly appropriate in use in mobile and IoT platforms. InceptionV3 and VGG16 were also effective, but more computing resources were needed. These findings indicate the tradeoff between accuracy and efficiency, and indicate that it is necessary to select models depending on limits of deployment.

This work is new since models are evaluated not only based on their classification accuracy, but based on their computing efficiency and ease of deployment as well. This is a method of closing the gap between laboratory experiments and practical use in agriculture.

The future studies are to expand this framework to field data. These data usually have noisy, imbalanced and diversified image conditions. Addressing the issue of class imbalance by using augmentation or generative algorithms such as GANs would enhance resilience. New Vision Transformers that exhibit fine balance between accuracy and efficiency should also be researched by the researchers such as EfficientNet, ShuffleNet and other lightweight architectures. The explainable AI approaches, including SHAP or LIME, can provide an understanding of the models that can be used to establish trust among farmers in automated diagnosis. Lastly, the trained models can be included in mobile applications, drones, and IoT to enable real-time tracking of diseases and enable the use of the data in precision agriculture.

References

1. Agarwal, M., Gupta, S., & Tiwari, P. (2020). Plant disease detection using CNN and transfer learning. International Journal of Recent Technology and Engineering, 8(5), 1072–1078.
2. Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., ... & Asari, V. K. (2019). A survey on deep learning in medical imaging and agriculture. Neural Computing and Applications, 32(10), 13279–13329. https://doi.org/10.1007/s00521-019-04344-x
3. Baranwal, A., Sahu, S., Jaiswal, A., & Sinha, J. (2020). Convolutional neural networks for plant disease detection: A review. Journal of Plant Pathology, 102(3), 1243–1255.
4. Barbedo, J. G. A. (2018). Impact of dataset size and variety on the effectiveness of deep learning for plant disease classification. Computers and Electronics in Agriculture, 153, 46–53.
5. Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for plant diseases: Detection and visual explanation. Computers and Electronics in Agriculture, 145, 319–329.
6. Chen, J., Zhang, D., & Yang, Y. (2023). Vision transformers in agriculture: A survey. Computers and Electronics in Agriculture, 212, 108222. https://doi.org/10.1016/j.compag.2023.108222
7. Chouhan, S. S., Kaul, A., Singh, U. P., & Jain, S. (2019). Plant disease detection using deep learning and IoT. International Journal of Computer Science and Information Security, 17(4), 234–239.
8. Chowdary, K., & Hemanth, J. (2022). Deep learning-based leaf disease detection in crops using images. Agronomy, 12(10), 2395.

Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-3 | Issue-6 | June - 2025 | Page 217-227

9. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. International Conference on Learning Representations (ICLR).
10. EfficientRMT-Net. (2023). An efficient ResNet and transformer hybrid for disease detection. Sensors, 23(23), 9516. https://doi.org/10.3390/s23239516
11. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311–318.
12. Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases. Frontiers in Plant Science, 8, 1270.
13. Hasan, M. M., Islam, M. M., & Park, D. (2021). A lightweight CNN model for real-time plant disease detection on edge devices. IEEE Access, 9, 123456.
14. Hosen, M. M., & Islam, H. (2025). Aggrotech: Leveraging deep learning for tomato disease management. arXiv preprint arXiv:2501.12052.
15. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90.
16. Lin, K., Gong, L., Huang, Y., Liu, C., & Pan, J. (2019). Deep learning for automated weed detection and crop disease recognition. Frontiers in Plant Science, 10, 1422.
17. Liu, J., Wang, X., & Ma, Y. (2020). A deep learning-based approach for automated diagnosis of plant diseases. Plant Methods, 16(1), 135.
18. Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.
19. MoSViT. (2025). A lightweight vision transformer framework for efficient disease detection. Frontiers in Artificial Intelligence.
20. Pandiyaraju, M., et al. (2024). A channel attention-driven hybrid CNN framework for paddy leaf disease detection. arXiv preprint arXiv:2407.11753.
21. Picon, A., Seitz, M., Alvarez-Gila, A., Mohnke, P., & Ortmann, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161, 280–290.
22. Singh, U., Chandel, N. S., & Kumar, P. (2020). Plant disease detection using deep learning: A review. International Journal of Computer Applications, 975, 8887.
23. Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture, 4(1), 41–49.
24. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 319–329.
25. Tan, M., & Le, Q. (2020). EfficientNet: Rethinking model scaling for convolutional neural networks. International Conference on Machine Learning (ICML).
26. 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.

27. Upadhyay, A., Chandel, N. S., Singh, K. P., Chakraborty, S. K., Kumar, M., ... & Elbeltagi, A. (2025). Deep learning and computer vision in plant disease detection: A comprehensive review. Artificial Intelligence Review. https://doi.org/10.1007/s10462-024-11100-x
28. Xie, C., Zhang, J., Li, R., Li, J., & Xu, J. (2020). Multi-level learning for fine-grained crop disease recognition. IEEE Access, 8, 18373–18383.
29. Yao, Z., & Huang, M. (2024). Deep learning in tropical leaf disease detection: Applications and advantages. Tropical Plants.
30. Yuan, Q., Li, Y., & Wu, H. (2022). A survey of lightweight deep learning models for mobile and edge devices in agriculture. Sensors, 22(18), 6801.
31. Zhang, S., Wang, X., & Zhao, Y. (2022). Plant disease classification using hybrid CNN-transformer models. Expert Systems with Applications, 198, 116846.
32. Zhang, Y., Li, Z., & Chen, F. (2023). Multi-task deep learning for joint disease detection and severity estimation in crops. Expert Systems with Applications, 211, 118578.