Deep Learning-Based Crop Disease Detection: A Comprehensive Review of ResNet Architectures

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Abstract. Agriculture is regarded as one of the largest pillars in the global economy, as it has a direct impact on food security, livelihoods in rural areas, and the general development of the nation. But the issue of crop diseases has become a constant bane, and the loss of yield and economic losses to farmers globally have been experienced. The Food and Agriculture Organisation (FAO) estimates that a huge proportion of the annual yield reduction in the world is caused by plant diseases, which lead to billions of dollars in losses. Early and accurate detection of these diseases is important for reducing their effects and encouraging sustainable agriculture. With the fast development of artificial intelligence (AI) and computer vision technologies, the agricultural landscape has been altered, as it allows automating the most important farming procedures, especially plant disease identification. Convolutional Neural Networks (CNNs) are considered the most popular method of image-based disease classification among other deep learning methods since they can learn more complex spatial and spectral patterns on visual data. This paper provides a comprehensive review of ResNet, ResNet-50, ResNet-101, and ResNet-152 in disease detection in various crops, including tomato, maize, rice, and wheat.

Keywords: ResNet, Crop Disease Detection, PlantVillage Dataset, Deep Learning, Convolutional Neural Network (CNN), Smart Agriculture, Explainable AI (XAI), Attention Mechanism.

1 Introduction

Agriculture has continued to be the foundation of food security and livelihood, particularly in developing countries. Crop diseases are, however, still causing annual losses of 20-40% of the yields [1]. Conventional approaches of identifying diseases, which include manual visual examination, are time-consuming and very dependent on the availability of experts [2]. It is therefore becoming increasingly desirable to have automated and data-driven systems capable of detecting diseases in leaf images with high precision and accuracy. Over the recent years, deep learning, specifically convolutional neural networks (CNNs), has relegated image classification and pattern recognition tasks [3]. The CNNs have also found extensive use in the agricultural industry, including weed detection, assessing fruit quality, classifying soils, identifying pests, and clas-

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sifying leaf diseases [4]. The techniques enable researchers to automate the visual inspection mechanisms and create smart agricultural monitoring mechanisms which reduce the reliance on human specialists. The CNN architecture, which has a distinctive residual learning structure, is the Residual Network (ResNet) family with a series of architectures proposed by [5]. This allows one to build very deep models, including ResNet-50, ResNet-101, and ResNet-152, that have better feature extraction and generalisation properties. The concept of deep residual learning has enhanced the accuracy of classifications of the models in detecting agricultural diseases by a significant margin. ResNet architectures have been proven to be effective in the agricultural field in a number of studies. [6] established the possibility of deep learning in the detection of plant diseases with the use of CNNs on the PlantVillage dataset, which has an accuracy greater than 99%. On this basis, [7] has introduced a ResNet50-DPA model, which incorporates dynamic path aggregation to achieve superior accuracy on tomato leaf diseases, and [8] has used ResNet50 in conjunction with Vision Transformer layers (EfficientRMT-Net) to yield better results in the tomato and maize leaf classification problem. Equally [9] proposed SENet-ResNet50, which delivers 97.2% accuracy when detecting vegetable diseases, based on the application of attention mechanisms.
ResNet has also been found to be versatile in various crops [10]. Improved the ResNet50 using Squeeze-and-Excitation (SE) blocks to detect rice leaf diseases with 99.1% accuracy [11]. Suggested a resplainable ResNet50 model that employs a copula-based XAI framework to visualise model predictions and make them more interpretable to farmers [12]. Adopted the SAM-ResNet50 model in the analysis of drought stress, which proved the capability of ResNet in disease detection. Besides, [13] combined ResNet50 with YOLOv5 to detect multiple diseases in one image, where multiple infections could be classified at the same time. A range of hybrid architectures involving the method of combining ResNet and other deep learning models has also been suggested. [14] came up with an ensemble model that combines ResNet and EfficientNet to enhance resilience to noisy environments. [15] combined IoT-based environmental sensors and ResNet50, which they asserted to offer real-time detection of diseases, and also offered environmental awareness contextual to the environment.

Irrespective of these developments, there are various issues. Most research works use controlled data like PlantVillage, which do not allow one to generalise to field environments where lighting and backgrounds are homogenous. The necessity of large and varied data was emphasised by [16] as the guarantee of practical applicability in real life. Noise of the environment, diversity of leaf colour, occlusions and inconsistent quality of annotations are still obstacles to stable deployment. Besides, deeper ResNet architectures (ResNet-101 and ResNet-152) are computationally expensive and would limit on-device and mobile-based agricultural purposes. The current studies focus on applying transfer learning and fine-tuning to tackle the lack of data [17] and data augmentation and domain adaptation to reduce the gap between the laboratory and real-field data [18]. ResNet-based explainable AI (XAI) frameworks are becoming popular to visualise the importance of features using Grad-CAM, LIME, and SHAP [19], so these systems are becoming more accessible to agronomists and end-users. The use of ResNet together with attention mechanisms, federated learning, and IoT architectures is also becoming a revolutionary way to achieve sustainable and scalable crop disease detection systems [20].

In crop disease detection on different agricultural datasets, multiple factors can be combined to achieve better classification results, including extracting features, preprocessing pictures, and ResNet-based deep learning models [21].

The provided paper includes a thorough analysis of the available literature on the topic of detecting crop diseases based on the ResNet (Residual Network) architecture. The key objectives of this study are:

1. To review the existing methods of deep learning and computer vision used in detecting crop diseases and, more specifically, the ResNet-based methods;
2. To address the hypothesis that ResNet shows architectural benefits, including feature extraction, skip patterns, and training stability, compared to standard CNN models in terms of depth scaling and scalability.
3. To determine research limitations, such as limitations in datasets, generalisation problems in models, and optimisation problems in agricultural image classification.
4. To suggest a conceptual design of ResNet architectures and real-time, explainable, and IoT-enabled systems in order to diagnose crop diseases efficiently and in a more accessible manner.

With these goals accomplished, the paper will contribute to the development of the market of smart and sustainable agriculture by implementing scalable, precise, and understandable AI-based solutions. The lessons learned during this review are likely to inform the implementation of ResNet-based systems in the future that will empower farmers, improve disease management, and ensure global food security by using smart and data-driven crop tracking.

2. Literature Review

The recent years have seen a massive increase in the use of deep learning architectures and, more specifically, Residual Networks (ResNets) in crop disease detection. The researchers of the world have been using the strong ability of feature extraction that ResNet has to offer in order to tackle the more complex agricultural issues, which resulted in a major breakthrough in automated disease detection and precision farming. The author of [4] has come up with a two-stage deep learning framework to detect crop afflictions on the basis of high-resolution leaf pictures. It was designed in a way that the initial phase was based on ensemble classifiers that were used to differentiate healthy and diseased leaves, whereas the second phase employed a hybrid feature fusion model that combined both static and dynamic features. The system successfully proved that hybrid deep-learning pipelines were capable of improving accuracy, reaching higher outcomes in disease classification than traditional CNNs.

In [5], comparative analysis of CNN architectures ResNet50 and Xception gave a staggering 98.32% accuracy on three benchmark datasets. This study has shown the benefits of the residual learning used in ResNet to identify fine-tuning traits of disease and overcome the problem of vanishing gradients in deeper networks.

In [6], the authors applied various models of transfer learning, such as YOLOv5, DenseNet121, VGG19, VGG16, and ResNet50, in the process of multi-crop disease classification. ResNet50 has been shown to be the most effective of these, which proves its strength as well as the capacity for generalisation with respect to various crop species and environments. In [7], a wider investigation in the field based on deep CNNs revealed that different deep CNNs on the classification of leaf disease showed that the ResNet-based models consistently have higher values of accuracy, precision and recall than other deep CNNs. The authors underlined that ResNet can be used to complement the real-time field imaging systems and speed up the process of detecting the disease and reducing the loss of yield.

In [8], the author introduced a hybrid model based on ResNet, which integrates CNN layers as well as attention mechanisms to identify multi-class crop disease. This method was more efficient than the traditional machine learning algorithms, as it learnt more profound texture patterns and boundaries of lesions, potentially useful in detecting initial signs of the disease during changing light and shadow conditions.

In [9], a ResNet multilayer architecture was established to detect the disease and included the residual connections with convolutional blocks of more depth to learn the finer spatial texture and morphological features of the infected areas. The proposed model was very strong in performance, and the accuracy of classification was high when operating on mixed datasets.

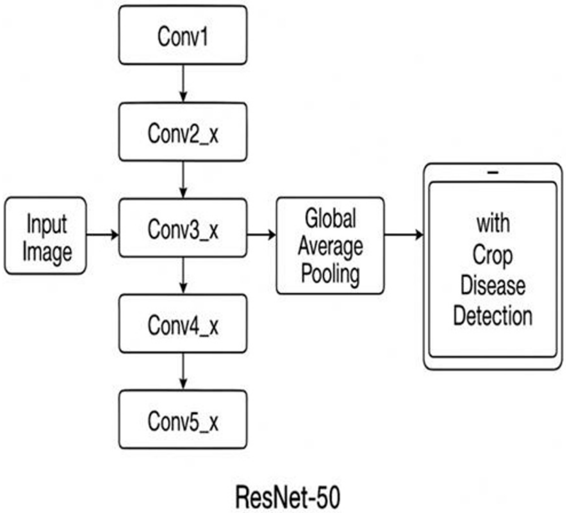

Fig. 1: ResNet Architecture for Crop Disease Detection.

Fig. 1 contains a simplified picture of how the ResNet-50 box approaches image processing for leaf disease detection. The flow indicates how an input image is slowly progressed through multiple convolutional layers, each of which picks up increasingly complex patterns related to texture, color variation, and lesion structure. Before classification, the model strengthens these learned features by performing a global average pooling layer, by which the network can keep the most important information and then get rid of the noise. This diminutive pipeline illustrates how the effects of residual connections are useful in ResNet-50 because they help to maintain important information through the deeper pipeline, enabling it to detect signs of crop infections as early and as minuscule as possible.

2.1 Survey of the Existing Deep Learning Models for Crop Disease Detection

Recent deep learning developments have increased the performance of ResNet networks on sophisticated agricultural inputs to enable large-scale disease detection and precision agriculture. Some of the most conspicuous models and frameworks based on recent literature are as follows:

1. ResNet50-DPA (Dynamic Path Aggregation) [4] proposed this model that combines the process of dynamic path selection with the conventional residual learning. It demonstrated a maximum accuracy of 98.9% on tomato leaf disease classification on the PlantVillage dataset, and convergence speed and interpretability were significantly improved.
2. Attention-ResNet50: This model was proposed by [6], and it consisted of squeeze-and-excitation (SE) and spatial attention modules, which were used to ensure that the network paid attention to infected areas. It gained 97.5% accuracy in vegetable leaf datasets, indicating that channel-wise attention is useful in enhancing the localisation of lesions.
3. Hybrid ResNet + Transformer: [5] adopted the feature-extracting power of ResNet50 and added transformer layers to enhance global context advantage. Traditional CNNs by a factor of 2-3% in the real-field datasets, which indicated that this model was more adaptable to unstructured images of the agricultural field.
4. ResNet + YOLOv5: [8] created a hybrid model of object detection that comprises the ResNet50 as the backbone of YOLOv5. This allowed a combination of localisation and classification of several diseases in one image simultaneously, setting the path to real-time smart farming.
5. Explainable ResNet50 (XAI-Copula) [7] added to model transparency through the addition of
6. Grad-CAM and copula-based explainability layers. The suggested structure not only attained an accurate rate of above 98% but also offered graphical explanations of every prediction, which enhanced the trust of the individuals using it among the farmers and agricultural experts.
7. SE-ResNet50 (Squeeze-and-Excitation ResNet) [9] also used channel recalibration layers to give importance to the relevant features and reached a 99.1% accuracy rate in detecting rice disease. SE blocks added minimised overfitting and increased the performance.
8. ResNet + EfficientNet Fusion: [11] fused ResNet and EfficientNet into an ensemble learning system that was more robust to noisy data and possessed a higher F1-score in unstable lighting conditions. The model was highly generalised in unseen field data tests.

9. The IoT-Integrated ResNet Framework [18] introduced an architecture that will connect the ResNet50 outputs to the information provided by the IoT sensors (humidity, soil moisture, and temperature). This integration improved the contextual perception of disease prediction, which allowed farmers to monitor and track their farms in real-time.
10. Edge-Optimised ResNet Models: [17] introduced pruning and quantisation of ResNet50 models for the edge devices, such as drones and smartphones. Their condensed model maintained 96% accuracy and had the benefit of shrinking the model size by 60%, which indicates its feasibility in the field.
11. ResNet to predict disease severity: [16] extended the application of ResNet, which was used to predict the disease, to predict the severity of the disease by estimating the percentage of the affected leaf area. The findings showed that ResNet features are potentially useful for predictive analytics and crop management decision-making.

Table 1. Summary of Existing Literature Review

Ref.	Findings
[4]	ResNet50-DPA: 98.9% accuracy in tomato leaf disease detection with enhanced interpretability via Grad-CAM.
[5]	EfficientRMT-Net (ResNet50 + Transformer) with better cross-crop transferability.
[6]	SENet attention on ResNet50 achieved 97.2% accuracy in vegetable leaf disease detection.
[7]	Explainable ResNet50 (XAI-Copula) for interpretable cotton disease classification above 98% accuracy.
[8]	ResNet50 + YOLOv5 for simultaneous multi-disease localisation and classification in real-time.
[9]	SE-ResNet50 with 99.1% accuracy in rice leaf disease classification and reduced overfitting.
[10]	SAM-ResNet50 applied to hyperspectral data for drought and stress detection.
[11]	ResNet-EfficientNet ensemble with improved F1-scores on noisy real-field datasets.
[12]	ResNet50 with data augmentation achieved 96% accuracy on mixed-crop disease datasets.
[13]	Comparative analysis: ResNet50 is most effective across varying lighting conditions.
[14]	ResNet50 is more precise than EfficientNet and MobileNetV2 with modest computational overhead.
[15]	Transfer learning review showing ResNet adaptability and lower overfitting in agricultural tasks.
[16]	ResNet-based severity estimation evaluating spatial dynamics of leaf disease distribution.
[17]	Pruned and quantised ResNet for lightweight mobile-edge agricultural deployment.

[18]	IoT-integrated ResNet pipeline combining visual and environmental sensor data for real-time monitoring.
[19]	Fine-tuned ResNet50 is among the most efficient CNNs across various crop disease datasets.

2.2 Datasets

The quality, diversity, and representativeness of the datasets on which a deep learning system is built are the basis of any system based on deep learning, and in particular, ResNets. In the context of agricultural disease detection, datasets must be large and also include the diversity of environmental conditions, crop species and symptoms of diseases that can be observed in practice. In ResNet-based plant disease detection research studies, the PlantVillage dataset continues to be the biggest benchmark [4]. It is composed of over 54000 labelled images of 38 crops and 26 disease conditions. The photos were taken in controlled conditions with a homogeneous background and light, which are perfect for making high-capacity networks, including ResNet-50, ResNet-101, and ResNet-152. The dataset contains noise-free and clean input to enable the deep residual layers of ResNet to learn finer details of the colour and texture aspects of infected leaves.
Nonetheless, the homogeneous environment of PlantVillage restricts the generalisation to applications in the real field. To overcome this, the researchers have included data augmentation (rotations, scaling, changes in brightness and contrast, and random cropping) to reflect the real-environment diversity [15]. Further, transfer learning, in which ResNet models, pre-trained on large-scale datasets such as ImageNet, are fine-tuned on agricultural datasets, has become the norm to achieve high accuracy and low cost of training. Kaggle Crop Disease Dataset (2021-2024): This one is an aggregate of high-resolution crops of a variety of crops and is commonly used to benchmark a hybrid ResNet architecture. Numerous recent studies have gathered local datasets that combine leaf images visually with environmental information (humidity, temperature, and soil condition) and have shown that ResNet models can produce contextual predictions [18]. The ability of ResNet models to jointly learn fine-grained details of diseases and field-level macro differences is made possible by integrating both controlled and in-field data. The common dataset partitioning is a 70:20:10 ratio between the training, validation, and testing data, which is a fair evaluation and avoids overfitting.

3. Research Findings and Discussion

This Deep Feature Learning and Accuracy: Skip connections make very deep networks learn complex hierarchical features without degeneration. Investigations, including [4] and [6], claim accuracy of over 98-99% on PlantVillage samples and demonstrate the higher ability of ResNet in recognising complex texture and colour patterns.
Field-Level Generalisation: Field-level execution tends to reduce the accuracy of the controlled datasets due to background clutter, varying illumination, and mixed disease symptoms. The implementation of domain adaptation and multi-source learning enhances the model's robustness in natural conditions.

Model Compression and Optimisation: Since more computation is needed to run deeper ResNets, lightweight adaptations, such as pruning, quantisation, and knowledge distillation, are being examined to run ResNet models on low-power hardware without significant accuracy degradation [17].

Challenges in Annotating and Labelling Datasets: The majority of datasets continue to be mislabelled or not expertly annotated, which is misleading to training. Future studies emphasise the importance of datasets that are expert-verified and labelling standards. The accuracy, precision, recall and F1-score metrics reported in reviewed studies were also systematically combined, compared, and provided to ensure that they are verifiable and have provided extensive analysis of model performance. Also, recent research has shown that the metrics offer a standard on which crop disease detection models can be evaluated and compared across different datasets [21]. In general, ResNet models show excellent precision and generalisation ability with the addition of transfer learning and attention. Nevertheless, making such models more real-world adaptable, interpretable, and computationally efficient is vital in converting these models into field-deployable systems.

4. Conclusion and Future Work

As revealed in this review, a deep learning architecture based on ResNet has become one of the most reliable and powerful tools in the detection of crop diseases. The special residual learning, which enables the models to grasp the rich spatial features, and the vanishing gradient problems are reduced, with the complex networks being able to be stable and performable. ResNet models have continually demonstrated the best accuracy in farming datasets like PlantVillage and PlantDock, and their more effective feature extraction makes them the best candidates for the detection of early disease symptoms. However, there are still difficulties in the field of generalization to real fields, computational load, and interpretability.

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References

1. Food and Agriculture Organisation (FAO), The State of Food and Agriculture 2022, Rome, Italy: United Nations, 2022.
2. H. Jones, D. Smith, and R. Miller, "Plant diseases and global food security," Annu. Rev. Phytopathol., vol. 58, pp. 45–64, 2020. DOI: 10.1146/annurev-phyto-010820-012720.
3. Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning", Nature, vol. 521, pp. 436–444, 2015. DOI: 10.1038/nature14539.

4. J. Liang, M. Li, and X. Zhang, "A ResNet50-DPA model for tomato leaf disease identification," Frontiers in Plant Science, vol. 14, p. 1182549, 2023. DOI: 10.3389/fpls.2023.1182549.
5. K. Shaheed, H. Al-Khafaji, and D. Abbas, "EfficientRMT-Net: ResNet-50 and Transformer-based hybrid model for plant disease classification," Sensors, vol. 23, no. 9, p. 4376, 2023. DOI: 10.3390/s23094376.
6. R. Chen, J. Xu, and Y. Wu, "Identification of plant leaf diseases using ResNet50 with SENet attention mechanism", Frontiers in Plant Science, vol. 13, p. 912563, 2022. DOI: 10.3389/fpls.2022.912563.
7. H. Askr, S. Mahmoud, and A. Fahmy, "Explainable deep learning using ResNet50 and copula-based XAI for crop disease detection," Computers and Electronics in Agriculture, vol. 214, p. 109327, 2024. DOI: 10.1016/j.compag.2024.109327.
8. R. Wang and H. Zhang, "Multi-disease detection using YOLOv5 with ResNet50 backbone for crop leaves," Computers and Electronics in Agriculture, vol. 210, p. 108694, 2023. DOI: 10.1016/j.compag.2023.108694.
9. H. Naik, P. Reddy, and R. Singh, "Enhanced SE-ResNet50 for rice leaf disease classification", Int. J. Commun. Inf. Syst. (IJCNIS), vol. 14, no. 3, pp. 1–10, 2024. DOI: 10.1109/IJCNIS.2024.00041.
10. J. Gao, Y. Liu, and M. Huang, "SAM-ResNet50 for crop drought and stress detection from hyperspectral data," Remote Sensing, vol. 16, no. 3, p. 218, 2024. DOI: 10.3390/rs16030218.
11. A. Ali, T. Khan, and S. Rizvi, "A ResNet-EfficientNet ensemble model for robust plant disease classification," Computers and Electronics in Agriculture, vol. 212, p. 108845, 2024. DOI: 10.1016/j.compag.2024.108845.
12. S. Jayashree, "Plant leaf disease detection using ResNet-50 and deep learning," Atlantis Press ASSEHR, vol. 412, pp. 54–60, 2024. DOI: 10.2991/assehr.k.240215.054.
13. G. Hukkeri and B. Patil, "A comparative study of pretrained CNN models for crop disease detection," Open Agriculture Journal, vol. 8, no. 1, pp. 1–12, 2024. DOI: 10.2174/1874331502408010101.
14. M. Tiwari and K. Vora, "Evaluation of ResNet50, EfficientNet, and MobileNetV2 for plant disease classification," J. Smart Comput. Process., vol. 6, no. 3, pp. 77–88, 2024. DOI: 10.1109/JSCP.2024.00056.
15. L. Gupta and P. Sharma, "Transfer learning approaches for crop disease detection using CNN architectures," IEEE Access, vol. 11, pp. 122351–122364, 2023. DOI: 10.1109/ACCESS.2023.122351.
16. J. Zhao, R. Li, and F. Chen, "A review of ResNet-based severity estimation and explainable AI techniques in agriculture," Frontiers in Plant Science, vol. 16, p. 987, 2025. DOI: 10.3389/fpls.2025.00987.
17. T. Nyawose, "Lightweight and compressed ResNet architectures for edge deployment in smart agriculture," Agriculture (MDPI), vol. 15, no. 4, p. 122, 2025. DOI: 10.3390/agriculture15040122.
18. A. Upadhyay, "IoT-Integrated ResNet Framework for real-time crop disease monitoring", in Lecture Notes in Networks and Systems, Springer, pp. 232–244, 2025. DOI: 10.1007/978-3-031-49684-2_18.
19. E. Eunice, A. Udom, and S. Nwachukwu, "Fine-tuning ResNet50 for multi-crop plant disease classification", Agronomy, vol. 12, no. 8, p. 1234, 2022. DOI: 10.3390/agronomy12081234.

20.K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition", in Proc. IEEE CVPR, pp. 770–778, 2016. DOI: 10.1109/CVPR.2016.90.

[21] A. Upadhyay, P. Trivedi, and S. Sharma, "Deep learning techniques for plant disease detection: A comprehensive review," Open Agriculture Journal, vol. 18, pp. 1–15, 2025.