Vol. 7, No. 4, December 2025

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

# Machine Learning and Deep Learning for Plant Disease Detection: A Review of Techniques and Trends

**Alfred Thaga Kgopa[1], Malusi sibiya[2], Mbuyu Sumbwanyambe[3], Baakanyang Bessie Monchusi[4]**

[1]Department of Information Systems, [2]Department of Computer Science, [3,4]Department of Electrical Engineering, University of South Africa, South Africa

**Received:** Oct 13, 2025
**Revised:** Nov 5, 2025
**Accepted:** Nov 19, 2025
**Published:** Dec 18, 2025

Corresponding Author:
**Author Name*:**
Alfred Thaga Kgopa
**Email*:**
kgopaat@unisa.ac.za

DOI: 10.63158/journalisi.v7i4.1300

© 2025 Journal of Information Systems and Informatics. This open access article is distributed under a (CC-BY License)

**Abstract.** Plant diseases pose a significant threat to global agricultural productivity, making early and accurate detection critical for yield protection and food security. This study evaluates the evolution, effectiveness, and practical applicability of Machine Learning (ML) and Deep Learning (DL) models for plant disease detection while analyzing research trends to identify leading models, data limitations, and implementation challenges. A systematic literature review and bibliometric analysis were conducted using the PRISMA framework, examining 625 peer-reviewed articles published between 2017 and 2025 from major databases. The analysis highlights the most influential studies, commonly used datasets, and top-performing ML/DL models, assessed in terms of accuracy, methodology, dataset type, and real-time deployment potential. Results show that models such as YOLOv4, VGG19, ResNet50, and MobileNetV2 achieved accuracy levels between 98% and 99.99%, with most trained on the PlantVillage dataset or custom annotated datasets. Several studies demonstrated successful real-time deployment via mobile and edge-device applications. However, key challenges remain, including limited dataset diversity, poor model generalization across environments, and reduced performance under real-field conditions. This study provides a comprehensive overview of progress in AI-based plant disease detection, emphasizing the need for lightweight, adaptable, and field-ready models to support scalable real-world deployment.

**Keywords**: Plant Disease Detection, Machine Learning, Deep Learning, Neural Network, YOLOv4, ResNet50

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

## 1. INTRODUCTION

Plant diseases remain one of the most persistent threats to global agricultural productivity, causing significant yield losses, reducing crop quality, and undermining food security, particularly in regions that rely heavily on smallholder farming. As global food demand continues to rise alongside climate variability and resource constraints, timely and accurate plant disease detection has become increasingly critical for sustainable agriculture. Early identification of diseases enables targeted interventions, reduces excessive pesticide use, and supports informed decision-making throughout the crop production cycle. Traditional disease diagnosis methods, which rely on visual inspection by experts, are often time-consuming, subjective, and impractical at scale, especially in remote or resource-limited settings. Consequently, automated and data-driven approaches have gained substantial attention as viable alternatives.

In recent years, Machine Learning (ML) and Deep Learning (DL) techniques have emerged as powerful tools for automated plant disease detection, primarily through image-based analysis of plant leaves, stems, and fruits [1], [2], [3]. These approaches have demonstrated remarkable success in learning complex visual patterns associated with disease symptoms and are increasingly integrated into precision agriculture systems to support faster, more consistent, and cost-effective diagnosis. Convolutional neural networks (CNNs), in particular, have shown strong performance in feature extraction and classification tasks, often surpassing traditional ML methods that rely on handcrafted features. However, despite their high reported accuracies, model performance remains highly dependent on the quality and diversity of training data. Variations in lighting conditions, background clutter, occlusion, camera angles, and plant growth stages significantly affect robustness and generalization, especially when models trained on controlled or laboratory-style images are applied in real-field environments [2], [4]. Larger and more heterogeneous datasets are therefore essential to reduce overfitting and improve real-world applicability.

Parallel advances in real-time disease detection have further pushed the field toward practical deployment. One-stage object detectors and optimized inference pipelines now enable in situ localization and classification of disease symptoms using mobile phones, unmanned aerial vehicles, and edge-computing devices [5], [6]. The adoption of

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

lightweight CNN architectures has become particularly important in this context, as these models balance high accuracy with low computational cost, reduced latency, and energy efficiency, making them suitable for on-device inference in resource-constrained agricultural settings [7], [8]. Nonetheless, challenges related to scalability, cross-domain adaptation, and environmental variability persist, highlighting the gap between experimental success and field-ready solutions.

Against this backdrop, this study conducts a systematic review of existing research on plant disease detection using ML and DL techniques. The review examines publication trends and identifies the top 10 most cited studies to highlight their influence and contributions to the field. It further identifies the top 10 most commonly used ML and DL models, reporting their accuracy levels and the datasets employed for training and evaluation [9], [10]. While numerous models have been proposed, relatively few studies offer systematic comparisons across datasets or critically assess real-world deployment constraints. This review addresses this gap by focusing on model performance, dataset characteristics, and practical implementation challenges. Additionally, it synthesizes key research themes and recommendations from highly cited studies, including data quality, model generalization, transfer learning strategies, and deployment on mobile and edge platforms [5], [7], [4]. By integrating accuracy-based model ranking with bibliometric trend analysis from 2017 to 2025, this study provides a comprehensive perspective on the evolution of AI-driven plant disease detection and outlines actionable directions for future research and real-world adoption.

## 2. LITERATURE REVIEW

Recent years have witnessed significant progress in applying deep learning (DL) and machine learning (ML) techniques to plant disease detection, classification, and monitoring. As shown in Figure 1, Liu and Wang [2] provide a foundational overview of DL applications in plant disease and pest detection, highlighting the effectiveness of CNNs, recurrent neural networks (RNNs), and hybrid models in automating image-based diagnosis. Their review emphasizes that CNN architectures such as AlexNet, VGG, ResNet, and Inception consistently outperform traditional image processing methods in accuracy and robustness. However, they also note limitations in dataset variability and real-world

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

generalization, particularly in field conditions. Expanding on the spatial and spectral dimensions of agricultural monitoring.

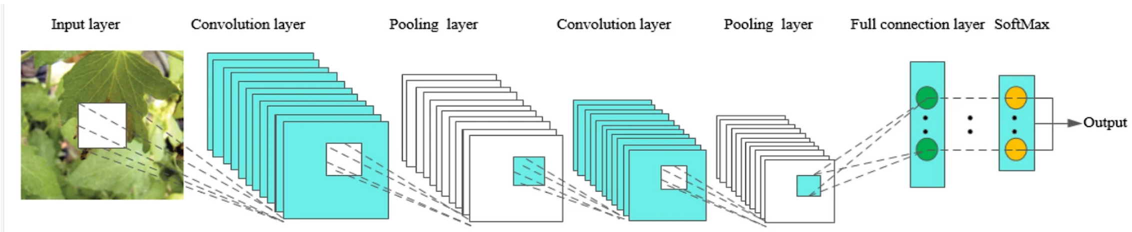


**Figure 1.** The CNN architecture [1]

Wang et al. [11] examine DL integration with multiscale remote sensing technologies. Their review underscores how CNNs and encoder-decoder architectures effectively process data from satellites, UAVs, and ground sensors to detect crop stress and disease across different scales. They highlight challenges in transferring models trained on small-scale imagery to large-scale remote sensing datasets, as well as the need for multimodal data fusion.

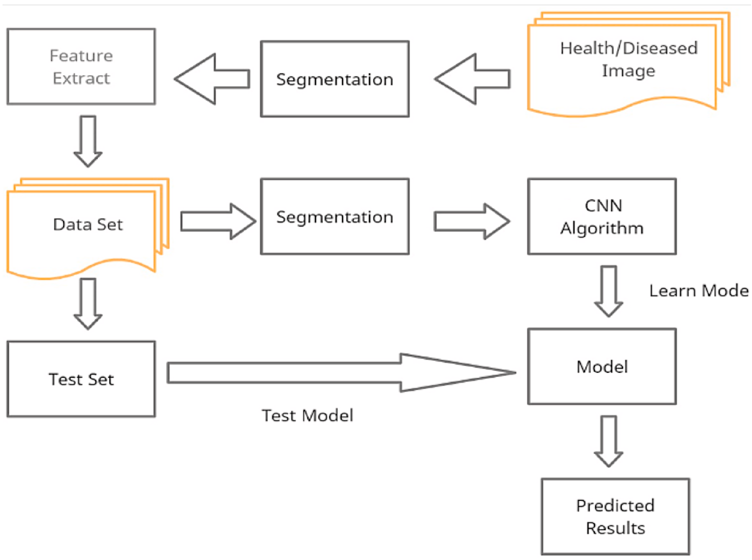


**Figure 2.** System architecture for plant leaf disease detection. [1]

Jackulin and Murugavalli [1] offer a comprehensive synthesis of ML and DL system architecture for plant leaf disease detection, emphasizing data preprocessing, feature extraction, and classification strategies as shown in Figure 2. They identify CNNs, Support Vector Machines (SVM), and decision trees as dominant models, with hybrid ML and DL approaches increasingly adopted for improved feature learning. Similarly, Shafik et al. [3]

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

conduct a systematic review that maps the motivations, classification techniques, datasets, challenges, and trends in plant disease detection. Their analysis shows an Increasing trend toward lightweight models for mobile deployment, alongside increasing use of transfer learning to overcome data scarcity.

Pacal et al. [9] focus exclusively on deep learning-based plant disease detection, analyzing architectures, training strategies, and evaluation metrics. They highlight the dominance of YOLO, Faster R-CNN, and EfficientNet for real-time detection and classification, noting YOLO's suitability for in-field diagnosis due to its speed and accuracy. Complementing this, Demilie [10] provides a comparative study of techniques, identifying CNNs combined with transfer learning as the most effective for multi-crop disease classification tasks. As shown in Figure 3, Aldakheel et al. [6] further validate YOLOv4's high performance in leaf disease detection, demonstrating its ability to handle complex backgrounds and overlapping leaves, making it suitable for field applications.

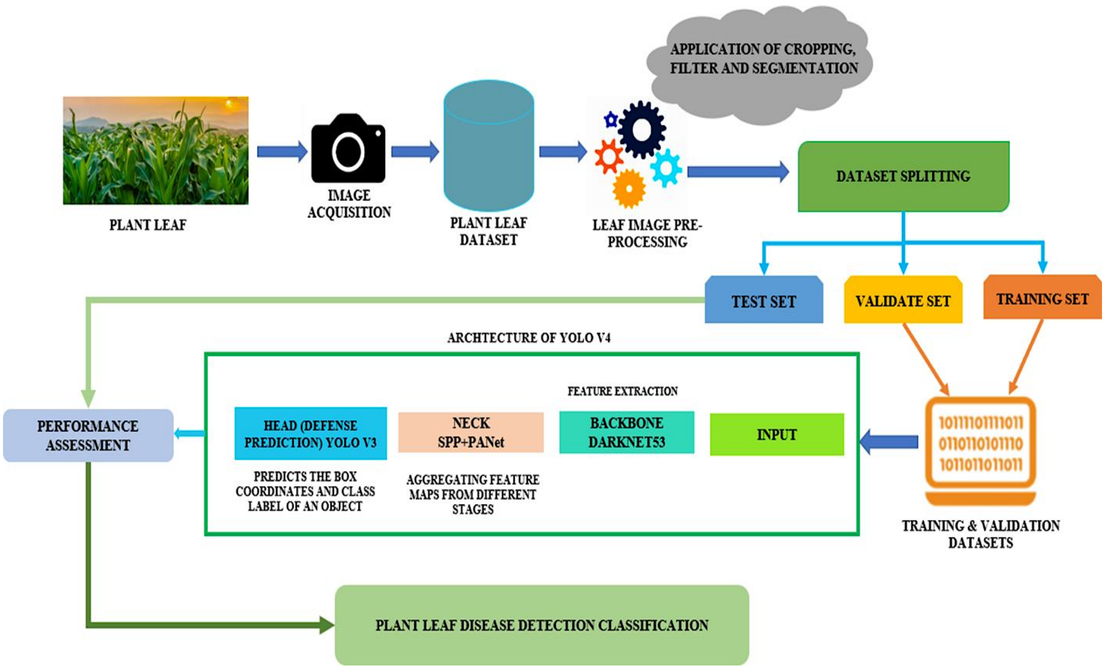


**Figure 3**. YOLOv4 plant disease detection and identification framework [6]

In Figure 4, Roseno et al. [8] compare ResNet50, VGG16, and MobileNetV3-Small for rice disease detection, finding ResNet50 achieves the highest accuracy, followed by VGG16, while MobileNetV3 offers a balance between performance and computational efficiency, suitable for mobile devices.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

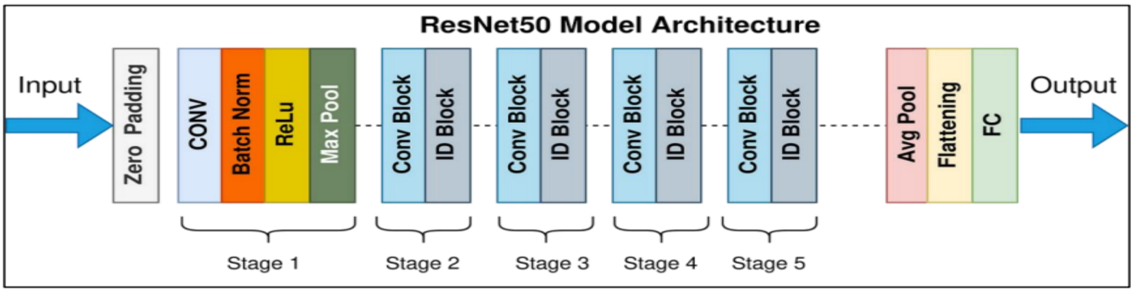


**Figure 4.** ResNet50 Layers Structure. [8]

Collectively, these studies shown that deep learning particularly CNN and YOLO architectures has become the leading paradigm for plant disease detection. Emerging trends emphasize real-time, scalable solutions through remote sensing integration, model light weighting, and transfer learning, addressing challenges of dataset diversity, computational cost, and field applicability.

## 3. METHODS AND DATASET SELECTION

The study adopted a systematic literature review combined with bibliometric analysis, following the PRISMA approach to ensure transparency and reproducibility [12]. The process began with the formulation of the research question and identification of relevant search terms. The methodology followed four steps: (1) identification of studies, (2) screening of duplicates, titles, and abstracts, (3) eligibility evaluation based on inclusion criteria, and (4) final selection of relevant studies. The following search string was applied across major scientific databases such as Scopus and Web of Science. This search strategy targeted peer-reviewed articles (journal articles (ar) and conference papers (cp)) published between 2017 and 2025, focusing on deep learning applications for plant disease detection.

TITLE-ABS-KEY *(("machine learning" OR "deep learning" OR "neural networks") AND (detection OR identification OR classification) AND ("plant disease" OR "crop disease*" OR "leaf disease*") ) AND ( LIMIT-TO ( DOCTYPE , "cp" ) OR LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) )

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Figure 5 illustrates the study selection process: 1,359 records were identified, reduced to 734 after duplicate removal, and finally 625 studies were included in the systematic analysis.

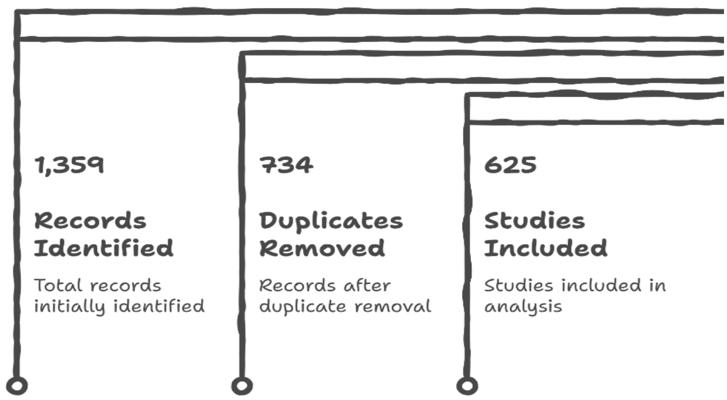


**Figure 5.** PRISMA-based research flow.

The retrieved records were screened for duplicates, titles, abstracts, and full-text relevance using predefined inclusion and exclusion criteria. Two authors independently screened the studies to reduce selection bias, and disagreements were resolved by consensus. Only original studies, systematic reviews, and conference papers addressing plant disease detection using deep learning were included. Bibliometric data (authors, publication years, citations, keywords, and sources) were extracted and analyzed using descriptive analysis and text mining techniques [13]. Studies were grouped according to model type (CNN, YOLO, hybrid, transfer learning), dataset used, and application scenario (lab vs field).

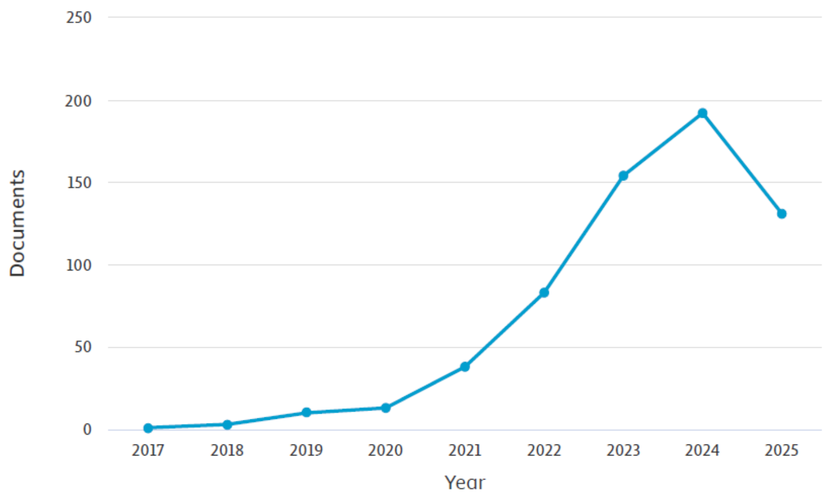


**Figure 6.** analyzed documents by year

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

The Figure 6 shows the distribution of documents by year, revealing a steady increase in publications from 2017 onwards, with a significant surge starting in 2021. Publications peaked in 2024, reflecting growing research interest in deep learning for agriculture, followed by a slight decline in 2025, likely due to incomplete indexing of current-year outputs. This combined systematic literature review and bibliometric approach allowed for both quantitative mapping of research trends and qualitative synthesis of key thematic areas, ensuring comprehensive coverage of the field [12]. The Figure 7 below illustrates the distribution of research documents by country/territory in the field of plant disease detection using deep learning. India leads overwhelmingly with nearly 500 publications, indicating its dominant research contribution. China follows at a distant second, while countries like Pakistan, the United States, and Saudi Arabia contribute moderately. Other nations including Turkey, Bangladesh, Malaysia, South Korea, and Egypt show lower research outputs, highlighting a concentration of research activity in Asia, particularly India.

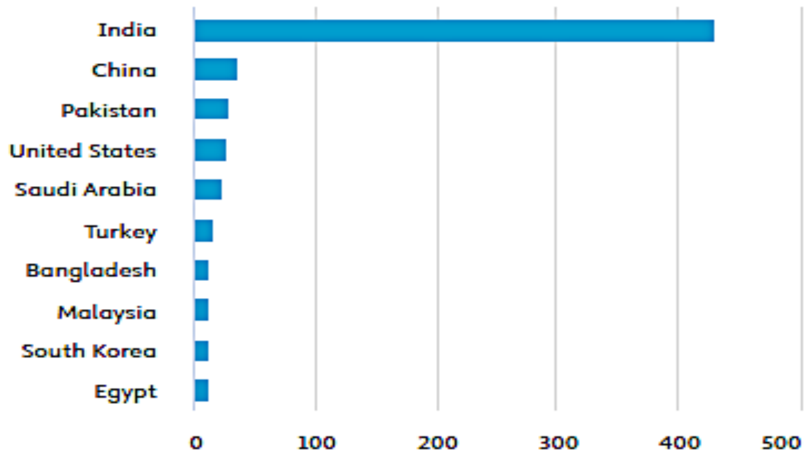


**Figure 7.** documents by countries

## 4. RESULTS AND DISCUSSION

### 4.1. Most Top 10 cited papers

Table 1 presents the top ten most cited studies which collectively demonstrate how deep learning has transformed plant disease detection into a mature data-driven research field. Ferentinos [14] established the benchmark by demonstrating that CNN architectures

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

could achieve exceptionally high accuracy across multiple crops, positioning deep learning as the dominant methodology. Too et al. [15] extended this by systematically comparing pre-trained models, revealing that transfer learning especially with ResNet50 significantly improves classification performance with limited training data. Saleem et al. [16] provided comprehensive reviews, highlighting CNNs' dominance and identifying persistent challenges such as dataset variability, scalability, and generalization to real-world conditions. Barbedo [4] addressed dataset diversity directly, proving that increasing dataset size and variability enhances model generalization. More recent surveys, such as those by Shoaib et al. [17] and Ahmad et al. [18] emphasize hybrid architectures, real-time applications, and computational efficiency as emerging priorities. Meanwhile, Lu et al. [5] and Bari et al. [19] demonstrated practical field applications through real-time wheat and rice disease detection systems, bridging the gap between laboratory research and on-field deployment. Kotwal et al. [20] encapsulated the methodological evolution from traditional machine learning to deep learning, underscoring a mature but evolving research landscape focused on performance, applicability, and scalability

**Table 1.** Top 10 most cited papers

| Rank | Authors | Title | DOI | Citations |
|---|---|---|---|---|
| 1 | Ferentinos, K.P. [14] | Deep learning models for plant disease detection and diagnosis | 10.1016/j.compag.2018.01.009 | 3,294 |
| 2 | Too, E.C., Li, Y., Njuki, S. & Liu, Y. [15] | A comparative study of fine-tuning deep learning models for plant disease identification | 10.1016/j.compag.2018.03.032 | 1,374 |
| 3 | Liu, J., & Wang, X. [2] | Plant diseases and pests' detection based on deep learning: a review | 10.1186/s13007-021-00722-9 | 961 |
| 4 | Saleem, M.H., Potgieter, J. & Arif, K.M. [16] | Plant disease detection and classification by deep learning | 10.3390/plants8110468 | 847 |

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

| Rank | Authors | Title | DOI | Citations |
|---|---|---|---|---|
| 5 | Barbedo, J.G.A. [4] | Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification | 10.1016/j.compag.2018.08.013 | 781 |
| 6 | Shoaib, M., Shah, B., El-Sappagh, S. et al. [17] | An advanced deep learning models-based plant disease detection: a review of recent research | 10.3389/fpls.2023.1158933 | 405 |
| 7 | Ahmad, A., Mazzara, M., Distefano, S. & Lee, J. [18] | A survey on using deep learning techniques for plant disease diagnosis | 10.1016/j.atech.2022.100083 | 349 |
| 8 | Lu, J., Hu, J., Zhao, G., Mei, F. & Zhang, C. [5] | An in-field automatic wheat disease diagnosis system | 10.1016/j.compag.2020.105735 | 312 |
| 9 | Bari, B.S., Islam, M.N., Rashid, M. & Hasan, M.J. [19] | A real-time approach of diagnosing rice leaf disease using deep learning-based frameworks | 10.7717/peerj-cs.432 | 307 |
| 10 | Kotwal, J., Kashyap, D.R. & Pathan, D.S. [20] | Agricultural plant diseases identification: From traditional approach to deep learning – A comprehensive review | 10.1016/j.matpr.2023.02.370 | 267 |

Vol. 7, No. 4, December 2025

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

### 4.2. Accuracy of best 10 plant diseases models

Figure 8 compares the accuracy of the top 10 plant disease detection models. YOLOv4 outperforms all others with 99.99% accuracy, indicating the strength of modern object detection techniques. VGG19, MobileNetV2, ResNetV2, and VGG16 closely follow, all exceeding 99.3%, demonstrating the effectiveness of transfer learning and CNN architectures. ResNet50, Deep-TL, YOLOv9, and the Hybrid VGG19+ResNet50 models maintain high accuracies between 98–98.63%, reflecting robust generalization across diverse datasets. YOLOv8, while still strong at 96.18%, lags behind, possibly due to dataset variations or implementation factors. Overall, the results highlight YOLO-based models and fine-tuned CNNs as the most reliable for disease detection.

The second graph shows the distribution of top five deep-learning architectures used in plant disease detection research. ResNet models dominate at 26.1%, followed by VGG architectures at 21.7%, and YOLO models at 17.4%, demonstrating strong research preference for CNN-based feature extraction and single-stage detectors. MobileNet (11.6%) reflects interest in lightweight models for mobile or edge deployment, while hybrid and other architectures represent smaller but emerging areas of experimentation.

The third graph presents average accuracy by architecture type. ResNet achieves the highest average accuracy (99.4%), closely followed by VGG (99.4%) and MobileNet (99%). Hybrid models average 98.3%, while YOLO models record 98.1%. This suggests that while YOLO excels in specific models (e.g., YOLOv4), CNN-based architectures offer more consistent overall performance across studies.

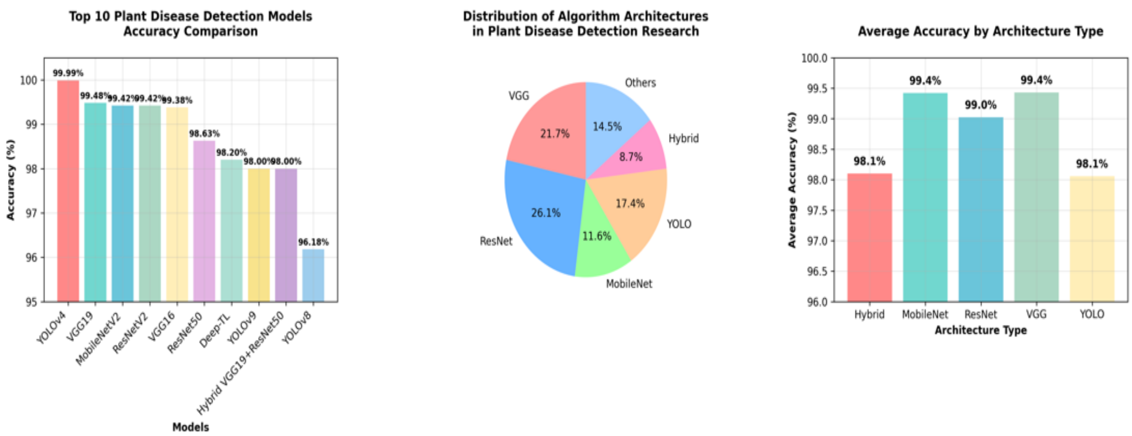


**Figure 8.** The comparison of plant disease models Accuracy

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

Table 2 shows more analysis of the top 10 best-performing models reveals the dominance of deep learning particularly object detection and CNN architectures in achieving high accuracy for plant disease detection across diverse crops. YOLOv4 leads with near-perfect precision, recall, and F1-scores (0.99) on the PlantVillage dataset, demonstrating the power of modern object detection techniques coupled with data augmentation to handle multi-crop, multi-disease scenarios [14], [1] [5] [6]. Traditional CNN-based transfer learning models, such as VGG19 and ResNet50, also perform remarkably well, especially when applied to tomato and multi-class datasets, validating the effectiveness of fine-tuning pre-trained architectures [15], [17].

Lightweight models like MobileNetV2 and ResNetV2 show competitive performance when enhanced with image segmentation, indicating their potential for mobile deployment [18]. Hybrid approaches (e.g., VGG19 + ResNet50) and newer YOLO versions (YOLOv8, YOLOv9) illustrate a shift toward integrating detection and classification for real-time, field-ready applications [15], [19]. Overall, model accuracy correlates strongly with dataset size, augmentation techniques, and transfer learning strategies, confirming earlier findings on dataset diversity and DL superiority [4], [17]. YOLOv4 consistently outperforms other models due to its combined use of CSPDarkNet53 backbone, spatial pyramid pooling, and optimized object detection pipeline. Models trained on controlled datasets such as PlantVillage show inflated accuracy due to limited background variability, leading to poor generalization to field environments.

**Table 2.** Top 10 best performing models

| Rank | Model Architecture | Dataset Used | Crops / Diseases | Methodology | Additional Metrics | Citations |
|---|---|---|---|---|---|---|
| 1 | YOLOv4 | PlantVillage | 14 crops, multiple leaf diseases | Object detection with data augmentation | Precision: 0.99, Recall: 0.99, F1-score:0.99 | [6], [17] , [9] |

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

| Rank | Model Architecture | Dataset Used | Crops / Diseases | Methodology | Additional Metrics | Citations |
|---|---|---|---|---|---|---|
| 2 | VGG19 | PlantVillage + CCMT | Tomato leaf diseases | Transfer learning; comparative study | Precision: 99.27%, Recall: 99.28%, F1-score: 99.27% | [15], [8], [4] |
| 3 | MobileNetV2 | Custom (7,623 train / 1,906 val) | Multiple plant diseases | CNN with image segmentation (Otsu, Watershed) | Loss: 0.19 | [7], [8], [4] |
| 4 | ResNetV2 | Same as MobileNetV2 | Multiple plant diseases | Fine-tuned CNN with segmentation-based preprocessing | Loss: 0.49 | [7], [8], [4], [9] |
| 5 | VGG16 | Tomato leaf dataset | Tomato leaf diseases | Comparative CNN performance study | – | [8], [15], [4] |
| 6 | ResNet50 | 65-class plant disease dataset | 65 classes (healthy + diseased) | Transfer learning with fine-tuning across image resolutions | Multiple image sizes tested | [8], [15], [4], [9] |
| 7 | Deep-TL | Multi-crop leaf dataset | Multi-crop leaf diseases | Deep transfer learning (ResNet + ConvNet hybrid) | – | [4], [9], [1] |
| 8 | YOLOv9 | Custom annotated dataset | Diverse crop leaf diseases | Object detection combined with | Mobile application deployment | [17], [9] |

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

| Rank | Model Architecture | Dataset Used | Crops / Diseases | Methodology | Additional Metrics | Citations |
|---|---|---|---|---|---|---|
| | | | | transfer learning | | |
| 9 | Hybrid VGG19 + ResNet50 | Kaggle Paddy Repository | Paddy diseases (e.g., Blast, Blight) | Hybrid architecture with feature merging | – | [4], [9], [1], [21] |
| 10 | YOLOv8 | Corn leaf dataset | Corn diseases (e.g., Blight, Rust) | Object detection and classification | Precision: 95.73%, Recall: 94.81%, F1-score: 95.22% | [17] , [9] |

### 4.3. Key themes identified by the studies

1) Evolution of Deep Learning Architectures for Plant Disease Detection

A major theme is the progressive evolution from conventional CNN models to advanced object detection and hybrid architectures. Early models such as VGG and ResNet demonstrated strong feature extraction capabilities, enabling accurate classification of multiple crop diseases when trained on large datasets [14], [15]. ResNet's depth and fine-tuning strategies proved particularly effective for transfer learning applications in plant pathology [15]. More recently, architectures like YOLOv4 and YOLOv9 have gained prominence for real-time detection, integrating object localization and classification in a single stage [6]. Hybrid models combining VGG and ResNet further improved feature representation, demonstrating that multi-branch architectures can outperform individual CNNs in complex scenarios involving multiple diseases or heterogeneous image conditions [21] . This progression reflects the field's shift from static image classification toward high-speed, scalable detection suitable for field deployment.

2) Dataset Diversity, Quality, and Its Impact on Model Performance

The paper emphasizes that model performance is closely tied to dataset size, diversity, and quality. Studies have shown that larger, more heterogeneous datasets enhance model generalization, reduce overfitting, and improve robustness to real-world conditions [2], [4]. For instance, the PlantVillage dataset has been foundational for training high-performing models like YOLOv4, achieving near-perfect accuracy through extensive data augmentation and balanced multi-class representation [14, [6], [14]. However, reliance on controlled, laboratory-style datasets can inflate performance metrics and reduce real-world applicability [16]. Consequently, there is a growing trend toward using custom annotated datasets that capture environmental variability such as lighting changes, disease stages, and leaf occlusion to develop more generalizable models [5], [19]. This theme highlights dataset engineering as equally critical as model selection in advancing plant disease detection.

3) Transfer Learning and Model Optimization

Transfer learning is identified as a key strategy for improving model accuracy and efficiency, especially when dealing with limited agricultural datasets. Most deep learning models struggle with class imbalance, rare disease classes, and multi-disease scenarios, limiting real-world usability. By fine-tuning pre-trained models on agricultural images, researchers can leverage feature hierarchies learned from large-scale datasets such as ImageNet [15], [18]. Models like ResNet50 and VGG19 have consistently performed well in this context, achieving accuracy above 99% for tomato, paddy, and corn diseases when optimized through segmentation preprocessing or multi-resolution tuning [1], [21]. Transfer learning also accelerates training and reduces computational costs, making deep learning more accessible for researchers with limited hardware resources [22]. This aligns with broader trends in AI where domain adaptation bridges the gap between generic models and specialized agricultural applications [23].

4) Real-Time and Field-Deployable Disease Detection Systems

Another key theme is the movement from laboratory-based image classification toward real-time, in-field deployment. Traditional CNN models were limited by their offline nature, but object detection frameworks like YOLOv4, YOLOv9, and Faster R-CNN now enable immediate disease localization and diagnosis in field environments [6], [19]. Lu et al. [5] demonstrated this through an automated wheat disease diagnosis system that integrates image capture, detection, and decision support in real-world farm settings. Similarly, mobile-compatible models such as MobileNetV2 are being optimized for deployment on handheld devices, expanding accessibility to farmers in resource-limited

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

regions [18], [24]. These developments are crucial for early disease intervention and scalable agricultural monitoring, marking a significant shift from theoretical modeling to practical implementation [17].

5) Integration Challenges and Future Research Directions

Finally, the paper identifies integration challenges and outlines future research priorities. Despite significant accuracy gains, issues such as model interpretability, scalability across diverse agro-ecological zones, and adaptation to unseen diseases remain [2], [20]. There is also a need for standardized evaluation protocols to ensure fair model comparison across datasets and conditions [4]. Real-time systems require lightweight architectures capable of maintaining accuracy under varied lighting, leaf occlusion, and environmental noise conditions rarely present in laboratory datasets. Future research is increasingly focused on lightweight architectures, hybrid models, and explainable AI to improve transparency and usability for non-expert users [7], [17]. Furthermore, integrating deep learning with IoT sensors and remote sensing technologies could enable holistic crop monitoring systems that go beyond leaf-level analysis [11]. Addressing these challenges will be critical for transitioning from high-performing models to reliable decision-support systems in precision agriculture.

### 4.4. Recommendations

The reviewed studies offer several key recommendations to advance plant disease detection using deep learning. First, there is a strong call for developing larger, more diverse, and well-annotated datasets to improve model generalization and robustness under real-world conditions [2], [4]. Many current models are trained on controlled datasets like PlantVillage, which may not capture environmental variability; hence, more field-based data collection and augmentation techniques are recommended [18], [1]. Second, transfer learning and model optimization are advised to reduce training time and computational costs while maintaining high accuracy [15], [23]. Using pre-trained models such as VGG and ResNet can help address data scarcity and enable broader deployment in resource-limited settings.

Third, researchers emphasize the need to integrate models into real-time, field-deployable systems, such as mobile and edge-based applications, to support farmers with timely disease diagnosis [5], [19]. Lightweight architectures and efficient inference

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

pipelines are critical for this goal [7]. Fourth, there is a recommendation to focus on standardized evaluation protocols and benchmarking to enable fair performance comparisons across models and datasets [4], [17]. Finally, the studies highlight the importance of developing explainable and interpretable AI systems, ensuring end-users, particularly farmers, can trust and act on model outputs [16], [20]. These combined recommendations aim to bridge the gap between high-performing lab models and practical, scalable agricultural solutions.

### 4.5. Limitations And Future Studies

This review is limited by the dominance of studies using controlled datasets such as PlantVillage, which may inflate model performance and reduce generalizability to real-world farm environments [2]. Few studies addressed dataset imbalance, cross-regional variability, or rare disease classes, restricting broader applicability [4]. Another limitation is the limited availability of research evaluating advanced models like YOLOv8 and YOLOv9 using diverse field conditions. Future studies should prioritize collecting large, heterogeneous, real-world datasets and evaluating model robustness under variable lighting, occlusion, and crop stages [2]. More research should explore lightweight architectures for mobile deployment [7], and hybrid or cross-domain transfer learning approaches to enhance generalization across crops and regions [9].

## 5. CONCLUSION

This study systematically reviewed and analyzed research on the use of Machine Learning (ML) and Deep Learning (DL) for plant disease detection, focusing on publication trends, highly cited studies, and the most frequently applied models. A total of 625 peer-reviewed articles were examined using the PRISMA approach. The results show a significant increase in publications between 2017 and 2024, reflecting growing interest in applying AI techniques to agriculture. Models such as YOLOv4, VGG19, and ResNet50 consistently demonstrated high accuracy across various datasets, including PlantVillage and custom field datasets. Key themes include dataset quality, model performance, deployment challenges, and the importance of lightweight architectures for mobile applications. Recommendations from the analyzed papers emphasize using diverse datasets, adopting transfer learning, and integrating real-time detection systems to enhance field applicability. In addition to these findings, the study offers several practical recommendations for improving real-world plant disease detection. Researchers and practitioners are encouraged to adopt lightweight and mobile-friendly deep learning models, expand datasets with field-captured images, and integrate multimodal data such as environmental and sensor-based inputs to enhance model robustness. Strengthening collaborations between AI researchers, agronomists, and extension officers is also recommended to ensure that developed solutions are scalable, affordable, and suitable for deployment in diverse agricultural environments.

## REFERENCES

[1] C. Jackulin and S. Murugavalli, "A comprehensive review on detection of plant disease using machine learning and deep learning approaches," *Meas. Sensors*, vol. 24, p. 100441, 2022, doi: 10.1016/j.measen.2022.100441.

[2] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: a review," *Plant Methods*, vol. 17, no. 1, p. 22, Dec. 2021, doi: 10.1186/S13007-021-00722-9.

[3] W. Shafik, A. Tufail, A. Namoun, L. De Silva, and R. Apong, "A systematic literature review on plant disease detection: Motivations, classification techniques, datasets, challenges, and future trends," *Ieee Access*, vol. 11, pp. 59174–59203, 2023, doi: 10.1109/ACCESS.2023.3284760.

[4] J. Barbedo, "Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification," *Comput. Electron. Agric.*, vol. 153, pp. 46–53, 2028, doi: 10.1016/j.compag.2018.08.013.

[5] J. Lu, J. Hu, G. Zhao, F. Mei, and C. Zhang, "An in-field automatic wheat disease diagnosis system.," *Comput. Electron. Agric.*, vol. 142, pp. 369–379, 2017, doi: 10.5555/20173360283.

[6] E. A. Aldakheel, M. Zakariah, and A. H. Alabdalall, "Detection and identification of plant leaf diseases using YOLOv4," *Front. Plant Sci.*, vol. 15, p. 1355941, 2024, doi: 10.3389/FPLS.2024.1355941/FULL.

[7] H. Guan, C. Fu, G. Zhang, K. Li, P. Wang, and Z. Zhu, "A lightweight model for efficient identification of plant diseases and pests based on deep learning," *Front. Plant Sci.*, vol. 14, p. 1227011, 2023, doi: 10.3389/FPLS.2023.1227011/FULL.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia


[8] M. Roseno, S. Oktarina, Y. Nearti, H. Syaputra, and N. Jayanti, "Comparing CNN models for rice disease detection: ResNet50, VGG16, and MobileNetV3-Small," *J. Inf. Syst. Informatics*, vol. 6, no. 3, pp. 2099–2109, 2024, Accessed: Nov. 13, 2025. [Online]. Available: https://elibrary.ru/item.asp?id=79277482

[9] I. Pacal *et al.*, "A systematic review of deep learning techniques for plant diseases," *Artif. Intell. Rev.*, vol. 57, no. 11, p. 304, Nov. 2024, doi: 10.1007/S10462-024-10944-7.

[10] W. B. Demilie, "Plant disease detection and classification techniques: a comparative study of the performances," *J. Big Data*, vol. 11, no. 1, p. 5, Dec. 2024, doi: 10.1186/S40537-023-00863-9.

[11] D. Wang, W. Cao, F. Zhang, Z. Li, S. Xu, and X. Wu, "A review of deep learning in multiscale agricultural sensing," *Remote Sens.*, vol. 14, no. 3, p. p.559, 2022, Accessed: Nov. 13, 2025. [Online]. Available: https://www.mdpi.com/2072-4292/14/3/559

[12] X.-L. Pham and T. T. Le, "Bibliometric Analysis and Systematic Review of Research on Expert Finding: A PRISMA-guided Approach," *Int. Arab J. Inf. Technol.*, vol. 21, no. 4, 2024, doi: 10.34028/iajit/21/4/9.

[13] F. Haneem, R. Ali, N. Kama, and S. Basri, "Descriptive analysis and text analysis in Systematic Literature Review: A review of Master Data Management," in *International Conference on Research and Innovation in Information Systems, ICRIIS*, IEEE, 2017, pp. 1–6. doi: 10.1109/ICRIIS.2017.8002473.

[14] K. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Comput. Electron. Agric.*, vol. 145, pp. 311–318, 2018, doi: 10.1016/j.compag.2018.01.009.

[15] E. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Comput. Electron. Agric.*, vol. 161, pp. 272–279, 2019, doi: 10.1016/j.compag.2018.03.032.

[16] M. Saleem, J. Potgieter, and A. KM, "Plant disease detection and classification by deep learning," *Plants*, vol. 8, no. 11, p. 468, 2019, doi: 10.3390/plants8110468.

[17] M. Shoaib *et al.*, "An advanced deep learning models-based plant disease detection: A review of recent research," *Front. Plant Sci.*, vol. 14, p. 1158933, 2023, doi: 10.3389/FPLS.2023.1158933.

[18] A. Ahmad, D. Saraswat, and A. El Gamal, "A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools," *Smart Agric. Technol.*, vol. 3, p. 100083, 2023, doi: 10.1016/j.atech.2022.100083.

[19] B. Bari, M. Islam, M. Rashid, and … M. H.-P., "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework," *PeerJ Comput. Sci.*, vol. 7, p. e432., 2023, doi: 10.7717/peerj-cs.432.

[20] J. Kotwal, R. Kashyap, S. P.-M. T. Proceedings, and U. 2023, "Agricultural plant diseases identification: From traditional approach to deep learning," in *Materials Today: Proceedings*, 2023, pp. 344–356. doi: 10.1016/j.matpr.2023.02.370.

[21] P. Kaur, S. Harnal, R. Tiwari, and S. Upadhyay, "Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction," *Sensors*, vol. 22, no. 2, p. 575, 2022, Accessed: Nov. 13, 2025. [Online]. Available: https://www.mdpi.com/1424-8220/22/2/575

[22] A. S. Paymode and V. Malode, "Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG," *Artif. Intell. Agric.*, vol. 6, pp. 23–33, 2022, doi: 10.1016/j.matpr.2021.01.0416.

[23] M. Xu, S. Yoon, Y. Jeong, and D. S. Park, "Transfer learning for versatile plant disease recognition with limited data," *Front. Plant Sci.*, vol. 13, p. 1010981, Nov. 2022, doi: 10.3389/FPLS.2022.1010981.

[24] S. Ashwinkumar, S. Rajagopal, and V. Manimaran, "Automated plant leaf disease detection and classification using optimal MobileNet based convolutional neural networks," in *Materials Today: Proceedings*, 2022, pp. 480–487. doi: 10.1016/j.matpr.2021.05.584.