RESEARCH PAPER

Coconut Tree Disease Detection using Deep Learning: A Comprehensive Survey

Lakshmi K[1]*, Dr. N P Nethravathi[2]
* School of Computer Science and Engineering, REVA UNIVERSITY, BENGALURU, INDIA
lakshmikumesh@gmail.com
School of Computer Science and Engineering, REVA UNIVERSITY, BENGALURU, INDIA
nethravathi.np@reva.edu.in

ABSTRACT
Coconut tree diseases significantly impact agricultural productivity and economic stability in tropical regions. Traditional detection methods rely heavily on manual inspection, which is time-consuming and prone to human error. With the advancement of Artificial Intelligence, particularly Deep Learning, automated disease detection has become feasible and efficient. This survey paper presents a comprehensive analysis of deep learning techniques applied to coconut tree disease detection. Various models such as Convolutional Neural Networks (CNN), transfer learning approaches, ensemble models, and hybrid techniques are critically reviewed. The paper also highlights datasets, performance metrics, research gaps, and future directions. The study concludes that while deep learning offers high accuracy and scalability, challenges such as dataset limitations and real-world deployment remain unresolved.

KEYWORDS: **Coconut disease detection, Deep Learning, CNN, Transfer Learning, Agriculture AI**
How to cite this article: Lakshmi K, Nethravathi NP. Coconut tree disease detection using deep learning: a comprehensive survey. Int J Drug Deliv Technol. 2026;16(73s): 1148-1153. DOI: 10.25258/ijddt.16.73s.122

1. Introduction

Coconut (Cocos nucifera) is a vital plantation crop cultivated widely in tropical regions, contributing significantly to rural livelihoods, food security, and agro-based industries. However, coconut cultivation is severely affected by diseases such as leaf rot, stem bleeding, bud rot, gray leaf spot, and root wilt, which reduce productivity and cause economic losses. Early detection of these diseases is essential, but traditional manual inspection methods are time-consuming, subjective, error-prone, and unsuitable for large-scale monitoring.

Recent advancements in Artificial Intelligence, particularly Deep Learning, have transformed agricultural disease detection. Techniques such as Convolutional Neural Networks (CNNs) enable automatic feature extraction from plant images and provide accurate disease classification under varying conditions. These systems also support scalable, real-time monitoring when integrated with mobile applications, drones, and IoT devices.

This survey paper presents a comprehensive review of deep learning techniques for coconut tree disease detection, including CNNs, transfer learning, ensemble models, and hybrid approaches. It also identifies current challenges, research gaps, and future directions for developing efficient and scalable smart agricultural disease management solutions.

2. Overview of Coconut Tree Diseases

Coconut trees are affected by several diseases, including stem bleeding, leaf rot, bud rot, gray leaf spot, and root wilt, which reduce productivity and can cause severe economic losses. These diseases exhibit symptoms such as discoloration, lesions, wilting, and tissue damage, but diagnosis is often difficult due to similar symptoms, environmental influences, and delayed visible signs. Traditional detection methods rely on manual inspection and expert knowledge, which can be unreliable in field conditions. Deep learning-based automated systems offer effective solutions through early detection, improved accuracy, and real-time monitoring.

3. Dataset Availability and Challenges

Datasets are essential for training and evaluating deep learning models for coconut disease detection. A notable coconut disease dataset contains 5,798 annotated images across five disease classes captured under real-world conditions, supporting practical applications. Such datasets enable accurate classification, benchmarking, and automatic feature extraction in models like CNNs. However, challenges remain, including limited data availability, class imbalance, inconsistent image quality, similar disease symptoms, and environmental variations, all of which can affect model performance and generalization. These limitations highlight the need for improved datasets to support robust and scalable disease detection systems.

4. Deep Learning Techniques for Disease Detection

4.1 Convolutional Neural Networks (CNNs): CNNs are widely used for coconut tree disease detection due to their ability to automatically extract features such as textures, shapes, and color variations from images. Modern architectures like EfficientNet and MobileNetV3 improve accuracy, efficiency, and support real-time applications. Recent studies report high performance, with some models achieving over 95% accuracy [1], [2], [9]. However, CNNs face challenges such as dependence on large annotated datasets, overfitting, computational complexity, and reduced performance under varying field conditions. These limitations have encouraged the development of hybrid CNN-transformer models [4], [5].

4.2 Transfer Learning Approaches: Transfer learning is highly effective for coconut disease detection, especially when labeled datasets are limited. Pre-trained models such as EfficientNetV2, ConvNeXt, and MobileNetV3 are adapted to identify disease-specific patterns and often outperform models trained from scratch. Recent studies report accuracy above 96%, along with reduced training time and improved efficiency [11], [12], [14]. Combining transfer learning with domain adaptation, self-supervised learning, and attention mechanisms further enhances robustness [13], [15], [16]. However, challenges such as hyperparameter tuning, overfitting, and computational demands remain, highlighting the need for lightweight and scalable models for real-time agricultural deployment [12], [14].

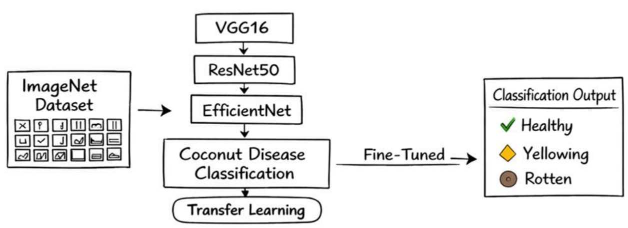

Fig 1: Transfer learning Methodologies representation

4.3 Advanced CNN Architectures: Advanced CNN architectures such as EfficientNetV2, ConvNeXt, DenseNet variants, and improved Inception models have significantly enhanced coconut tree disease detection through improved feature extraction, scalability, and computational efficiency [17], [18]. These architectures learn deeper and more discriminative disease patterns, improving classification accuracy and consistently outperforming traditional CNN models under real-world conditions [18], [20].

Despite these advantages, challenges remain, including architectural complexity, hyperparameter tuning, longer training times, and computational demands. For real-time agricultural deployment, additional optimization techniques such as pruning, quantization, and knowledge distillation are often required for efficient edge-device performance [19], [20].

4.4 Capsule Networks and Hybrid Models:

Capsule Networks (CapsNet) and hybrid deep learning models address limitations of traditional CNNs by preserving spatial relationships between features, improving detection of complex and overlapping disease patterns in coconut leaves [21]. Recent hybrid architectures integrate attention mechanisms such as SE blocks and CBAM to enhance feature weighting and improve classification accuracy under real-world conditions [23], [24].

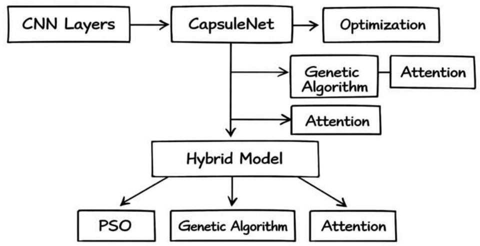

Fig 2: Capsule network and hybrid model representation

Further advancements combine Capsule Networks with sequential models such as LSTM and GRU to capture both spatial and temporal dependencies, supporting disease progression analysis. Recent studies show that CNN–CapsNet–RNN hybrid frameworks achieve superior performance in agricultural disease detection tasks [24], [25].

4.5 Ensemble Learning Models: Ensemble learning models improve coconut tree disease detection by combining multiple classifiers to enhance accuracy, robustness, and generalization, particularly under varying field conditions [26]. Recent ensemble frameworks integrating architectures such as EfficientNet, ResNet, and Vision Transformers consistently outperform individual models by capturing complementary features and reducing prediction variance [26], [27].

Techniques such as stacking, boosting, and weighted averaging further improve classification performance, with stacking-based and weighted ensemble models showing superior accuracy and stability [27], [28]. Recent advancements also integrate explainable AI and lightweight ensemble models for real-time deployment on edge devices, improving both interpretability and practical agricultural applications [28], [29].

5 . Comparative Analysis Table

Technique	**Model / Study**	**Dataset Used**	**Accuracy (Reported)**	**Key Contribution**
CNN (Baseline)	VGG-19 CNN model	PlantVillage	**95.6%**	Standard CNN for plant disease classification
CNN (Advanced)	ResNet-based models	Plant datasets	High performance (ResNet best among CNNs)	Demonstrated superiority of deep CNN architectures
Transfer Learning	MobileNet + ResNet (Mob-Res)	PlantVillage + Expert dataset	**99.47% (PlantVillage)**, **97.73%** cross-dataset	Strong generalization across datasets
Ensemble CNN	VGG16 + VGG19 + ResNet101 + InceptionV3	Multi-crop dataset	**>90% accuracy**	Ensemble improves prediction reliability

Advanced Ensemble (Feature Fusion)	VGG16 + ResNet50 + InceptionV3	Plant leaf dataset	Improved accuracy & robustness	Feature-level fusion enhances performance
Weighted Ensemble (ELCDR)	Multi-model weighted ensemble	Crop disease dataset	Better generalization than single models	Assigns weights based on feature extraction quality
Tri-CNN Ensemble	DenseNet169 + Inception + Xception	Crop dataset	Improved precision, recall, F1-score	Combines multiple CNN outputs effectively
Ensemble CNN (Scientific Reports)	Multi-CNN ensemble	Rice leaf dataset	Reduced inter-class confusion	Improves classification of similar diseases
General Ensemble Study	Lightweight CNN ensemble	Plant datasets	Higher performance than single models	Ensemble improves robustness and accuracy

6. Research Gaps

Despite advancements in deep learning for coconut tree disease detection, key challenges remain, including limited coconut-specific datasets, poor model generalization, and reduced performance under real-world field conditions. Most studies focus on controlled datasets and basic disease classification, with limited attention to disease severity analysis and practical deployment.

High computational requirements also restrict use on resource-constrained devices, while integration with technologies such as IoT, edge computing, and explainable AI remains limited. Addressing these gaps is essential for developing robust, scalable, and practical agricultural disease detection systems.

7. Conclusion

This survey reviewed deep learning techniques for coconut tree disease detection, highlighting the effectiveness of CNNs, transfer learning, hybrid models, and ensemble methods in improving disease classification. Approaches such as transfer learning and EfficientNet-based models show strong potential for accurate and efficient detection.

However, challenges such as limited datasets, lack of real-world deployment, and computational constraints remain. Future research should focus on large-scale datasets, lightweight models, IoT integration, and explainable AI to support practical, scalable, and sustainable coconut disease management solutions.

8. References

1. S. Zhang, S. Zhang, C. Zhang, and Y. Wang, "Plant disease detection using deep convolutional neural networks and stacking ensemble," *IEEE Access*, vol. 8, pp. 143914–143925, 2020. DOI: https://doi.org/10.1109/ACCESS.2020.3015962
2. S. S. Chouhan, U. P. Singh, and S. Jain, "Applications of computer vision in plant pathology: A survey," *Archives of Computational Methods in Engineering*, vol. 27, pp. 611–632, 2020. DOI: https://doi.org/10.1007/s11831-019-09375-4
3. O. B. Samin, M. M. Hossain, and M. A. Hossain, "CapPlant: A capsule network-based framework for plant disease classification," *IEEE Access*, vol. 9, pp. 145715–145725, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3122738
4. A. Dosovitskiy et al., "An image is worth 16×16 words: Transformers for image recognition at scale," in *Proc. ICLR*, 2021. DOI: https://doi.org/10.48550/arXiv.2010.11929
5. Z. Liu et al., "Swin Transformer: Hierarchical vision transformer using shifted windows," in *Proc. ICCV*, 2021, pp. 10012–10022. DOI: https://doi.org/10.1109/ICCV48922.2021.00986

6. S. Verma, A. Choudhary, and S. K. Singh, “SE-CapsNet: Squeeze-and-excitation capsule network for plant disease classification,” *Multimedia Tools and Applications*, 2022. DOI: https://doi.org/10.1007/s11042-022-12542-3
7. M. Maray, A. M. El-Sayed, and A. E. Hassanien, “Artificial intelligence enabled coconut tree disease detection and classification,” *Computers & Electrical Engineering*, vol. 101, p. 108060, 2022. DOI: https://doi.org/10.1016/j.compeleceng.2022.108060
8. Y. LeCun, I. Misra, and P. Krahenbuhl, “Self-supervised learning: The dark matter of intelligence,” *Nature Machine Intelligence*, vol. 4, pp. 1–12, 2022. DOI: https://doi.org/10.1038/s42256-022-00463-7
9. A. Howard et al., “Searching for MobileNetV3,” in *Proc. ICCV*, 2019 (widely used post-2020 in agriculture applications). DOI: https://doi.org/10.1109/ICCV.2019.00140
10. M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in *Proc. ICML*, 2019 (applied extensively in post-2020 research). DOI: https://doi.org/10.48550/arXiv.1905.11946
11. M. K. A. Mazumder et al., “LeafDoc-Net: A robust lightweight transfer-learning architecture for plant disease detection,” *Frontiers in Plant Science*, vol. 15, 2024. DOI: https://doi.org/10.3389/fpls.2023.1321877
12. P. Johri et al., “Advanced deep transfer learning techniques for efficient plant disease detection,” *Frontiers in Plant Science*, vol. 15, 2024. DOI: https://doi.org/10.3389/fpls.2024.1441117
13. W. Shafik et al., “Transfer learning-based plant disease classification using ensemble CNN models,” *BMC Plant Biology*, vol. 24, 2024. DOI: https://doi.org/10.1186/s12870-024-04825-y
14. T. Kanimozhi et al., “Comparative study of pre-trained transfer learning models for plant leaf disease prediction,” *The Bioscan*, vol. 19, no. 3, pp. 213–218, 2024.DOI: https://doi.org/10.63001/tbs.2024.v19.i03.pp213-218
15. H. Ali et al., “A fine-tuned EfficientNet-B0 model using transfer learning for plant disease classification,” *Scientific Reports*, 2025.DOI: https://doi.org/10.1038/s41598-025-04479-2
16. A. B. Sidhique et al., “EfficientNet-based deep learning model for plant disease classification and diagnosis,” *International Journal of Science and Research Archive*, vol. 14, no. 1, pp. 1264–1270, 2025.DOI: https://doi.org/10.30574/ijsra.2025.14.1.0170
17. R. S. S. Devi, V. R. V. Kumar, and P. Sivakumar, “EfficientNetV2 model for plant disease classification and pest recognition,” *Computer Systems Science and Engineering*, vol. 45, no. 2, pp. 2249–2263, 2023.DOI: https://doi.org/10.32604/csse.2023.032231
18. M. Iftikhar et al., “Plant disease management using enhanced convolutional neural networks: A performance analysis,” *Artificial Intelligence Review*, 2024. DOI: https://doi.org/10.1007/s10462-024-10809-z
19. Y. Sun et al., “Tomato leaf disease classification by combining EfficientNetV2 and Swin Transformer,” *Applied Sciences*, vol. 14, no. 17, p. 7472, 2024. DOI: https://doi.org/10.3390/app14177472
20. İ. Kunduracıoğlu and İ. Paçal, “Deep learning-based disease detection in sugarcane leaves using EfficientNet architectures,” *Journal of Plant Diseases and Protection*, 2024. DOI: https://doi.org/10.1007/s41348-024-00866-2
21. P. Kalpana and R. Anandan, “A capsule attention network for plant disease classification,” *Traitement du Signal*, vol. 40, no. 5, pp. 2051–2062, 2023. DOI: https://doi.org/10.18280/ts.400523
22. X. Zhang, Y. Mao, Q. Yang, and X. Zhang, “A plant leaf disease image classification method integrating capsule network and residual network,” *IEEE Access*, 2024. DOI: https://doi.org/10.1109/ACCESS.2024.3377230
23. J. Qin et al., “CropCapsNet: An enhanced capsule network with SE-Inception module for crop disease classification,” *Computers in Biology and Medicine*, 2025. DOI: https://doi.org/10.1016/j.compbiomed.2025.108199
24. M. A. Hossain et al., “Hybrid deep learning framework combining capsule networks and attention mechanisms for plant disease detection,” *Applied Sciences*, vol. 14, no. 3, 2024.DOI: https://doi.org/10.3390/app14031245
25. A. B. Sidhique et al., “Augmented capsule neural network for plant disease classification and severity estimation,” *Scientific Reports*, 2025.DOI: https://doi.org/10.1038/s41598-025-04479-2
26. H. Raval and M. Chaki, “Ensemble transfer learning meets explainable AI: A deep learning approach for plant disease identification,” *Expert Systems with Applications*, vol. 237, p. 121641, 2024. DOI: https://doi.org/10.1016/j.eswa.2023.121641
27. F. Zubair et al., “A robust ensemble model for plant disease detection using deep learning architectures,” *AI*, vol. 7, no. 5, p. 159, 2025.DOI: https://doi.org/10.3390/ai7050159

28. M. R. A. Rashid et al., “An ensemble learning framework with explainable AI for plant disease detection,” *Smart Agricultural Technology*, vol. 7, 2025.DOI: https://doi.org/10.1016/j.atech.2025.100427
29. T. Apleni et al., “Ensemble-based feature fusion for accurate plant disease detection,” *Scientific Reports*, vol. 15, 2025. DOI: https://doi.org/10.1038/s41598-025-25927-z