Early Detection and Diagnosis of Coconut Leaf Diseases in Sri Lanka's Coconut Triangle: A Systematic Review

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***Abstract*— This study presents a comprehensive Systematic Literature Review (SLR) on the early detection and diagnosis of coconut leaf diseases in Sri Lanka's Coconut Triangle, a region critical to the nation's agricultural economy. The review systematically evaluates published research on deep learning-based models, image classification techniques, and hybrid approaches that integrate environmental data for more reliable diagnosis. To ensure methodological rigor, the study followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. Relevant studies were retrieved from scholarly databases, including IEEE Xplore, ScienceDirect, Springer, Scopus, and Google Scholar, using predefined search strings. Strict inclusion and exclusion criteria were applied to filter peer-reviewed articles published between 2016 and 2025, ensuring relevance and reproducibility. A total of 20 papers met the criteria for final review, covering a diverse range of approaches such as Convolutional Neural Networks (CNNs), transfer learning models (VGG16, ResNet, EfficientNet), ensemble methods (CNN–SVM), and IoT-assisted systems. The synthesis of findings highlights several insights: transfer learning-based CNNs achieved over 90% accuracy, even for subtle early-stage symptoms. Hybrid approaches combining CNNs with classifiers like SVMs improved precision, reducing false positives and enhancing robustness across coconut varieties. Integrating environmental data (humidity, rainfall, temperature) increased accuracy by 6–10%, stressing the need for region-specific models in Sri Lanka's diverse agro-climatic zones. However, most systems lack large-scale field validation, mobile deployment, and consideration of smallholder farmer resource constraints. Key research gaps include limited Sri Lanka-specific datasets, inadequate focus on multi-disease co-infections, and the absence of farmer-oriented mobile and IoT tools for real-time disease monitoring. Finally, the study highlights future directions such as building larger and varietal-specific datasets, experimenting with advanced architecture (EfficientNet, Vision Transformers), and developing lightweight, offline-capable mobile applications to ensure accessibility for rural farmers. The integration of IoT sensors and climate forecasting models is also recommended to move from disease detection towards predictive and preventive farming strategies. This review contributes to the body of knowledge by not only consolidating existing research but also providing actionable insights for researchers, policymakers, and agricultural technology developers to ensure sustainable disease management and resilience in Sri Lanka's coconut sector.**

***Keywords*— Coconut Triangle, Leaf disease detection, Deep learning, CNN, Machine Learning, Support Vector Machine, Image classification**

I. INTRODUCTION

Coconut cultivation is vital to Sri Lanka's economy, culture, and rural livelihoods, particularly in the Coconut Triangle region (Kurunegala, Puttalam, and Gampaha). This region contributes a major share of the country's coconut production, supporting thousands of smallholder farmers. However, diseases such as Grey Leaf Spot, Leaf Blight, and Weligama Coconut Leaf Wilt have emerged as persistent threats, significantly reducing yields, lowering nut quality, and thereby impacting both household incomes and the national economy. If not detected and treated at an early stage, these diseases can spread rapidly, posing long-term risks to the sustainability of coconut farming.

Traditionally, disease identification has relied on manual inspection by farmers or agricultural officers. While this practice is low-cost and has been used for generations, it is also subjective, time-consuming, and prone to human error. More importantly, early-stage or multiple co-occurring infections are often missed, resulting in delayed or ineffective interventions. These shortcomings underline the urgent need for scientifically robust and technology-driven solutions to safeguard Sri Lanka's coconut sector.

In recent years, Deep Learning (DL) and Machine Learning (ML) techniques have shown significant promise in plant disease detection. Convolutional Neural Networks (CNNs) in particular have demonstrated strong performance in image-based classification, automatically identifying subtle features such as discoloration, lesion patterns, and texture variations. Hybrid approaches, such as combining CNN feature extraction with Support Vector Machines (SVMs), have further improved classification precision. Moreover, emerging studies suggest that incorporating environmental factors such as humidity, rainfall, and temperature can improve detection accuracy by up to 10%, making models more context-aware and region-specific.

Despite these advances, significant gaps remain in the application of such models to coconut leaf diseases in Sri Lanka. Many studies rely on non-local or generalized datasets, limiting their relevance to the Coconut Triangle's unique agro-ecological conditions. Additionally, limited attention has been given to the detection of multiple diseases simultaneously, which is crucial for real-world applications. Furthermore, while several proof-of-concept models exist, large-scale field trials, mobile-based farmer applications, and IoT-enabled deployments are still lacking.

Given these challenges, there is a strong need for a Systematic Literature Review (SLR) that consolidates and critically evaluates the existing body of knowledge. Unlike traditional reviews, an SLR ensures transparency, reproducibility, and comprehensiveness by following a structured methodology such as PRISMA. This paper, therefore, provides a systematic synthesis of research on coconut leaf disease detection, focusing on datasets, algorithms, model architectures, and evaluation metrics. The review also identifies research gaps, compares different approaches, and outlines future research directions to support practical, scalable, and sustainable solutions for Sri Lanka's coconut industry.

II.METHODOLOGY

This review adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure a structured, transparent, and reproducible approach. A comprehensive search was conducted across multiple academic databases, including IEEE Xplore, ScienceDirect, Springer, Scopus, and Google Scholar, using carefully designed search strings such as *"Coconut leaf disease detection," "Deep learning for coconut diseases," "CNN agriculture Sri Lanka,"* and *"Plant disease classification CNN SVM."* The search focused on peer-reviewed publications between 2016 and 2025, covering studies that specifically addressed coconut leaf diseases, employed ML or DL techniques, and reported quantifiable evaluation metrics.

Studies that dealt with non-coconut crops, were written in non-English languages, or did not present experimental results were excluded. After removing duplicates and irrelevant records, 20 studies were shortlisted for detailed review. Each selected study was analyzed based on dataset characteristics (size, classes, balance, and source), disease types investigated, algorithmic approaches, evaluation metrics, and practical implications, as well as reported strengths and limitations. This systematic process ensures that the findings of this review are comprehensive, evidence-based, and aligned with global best practices for conducting systematic reviews in agricultural technology research.

III. RESEARCH GAP

[1] Lack of region-specific models: Although DL models such as CNNs and transfer learning architectures have shown high accuracy in plant disease detection, most existing studies are based on non-local or generalized datasets collected from other countries or agro-climatic zones. This significantly limits their applicability to the unique conditions of Sri Lanka's Coconut Triangle, where environmental factors and disease progression patterns differ.

[2] Limited multi-disease detection: Current research predominantly focuses on detecting a single disease at a time. However, in practical field conditions, coconut leaves are often affected by more than one disease simultaneously, especially during the early stages when symptoms overlap. The inability to detect such co-occurring infections reduces the effectiveness of disease management strategies.

[3] Neglect of varietal differences: Sri Lanka is home to several distinct coconut varieties, such as SLT (Sri Lanka Tall) and CRIC hybrids, each with unique morphological and physiological traits. Existing models fail to account for these varietal differences, leading to reduced accuracy when generalized models are applied to region-specific datasets.

[4] Minimal integration of environmental data: Only a few studies have attempted to integrate environmental variables such as temperature, rainfall, humidity, or soil conditions into their models. Yet, these factors play a crucial role in disease onset and progression, and their omission results in less context-aware and less reliable prediction systems.

[5] Absence of farmer-oriented systems: While numerous studies have developed proof-of-concept models, there is still a lack of practical, farmer-friendly tools such as lightweight mobile applications, IoT-enabled sensors, or real-time alert systems. This gap highlights the disconnection between academic research and field-level implementation, ultimately limiting the impact on smallholder farmers.

IV. LITERATURE COMPARISON

Study	Model/Approach	Dataset	Accuracy	Strengths	Limitations
Huang et al. (2025) – Disease Infection Classificatio n	Enhanced VGG16 with transfer learning + SGD optimizer (Kaggle dataset)	Kaggle coconut dataset	97.7% (outperformed VGG16 93.1%, ResNet-34 84.3%)	High accuracy with enhanced VGG16	Non-local dataset (not region-specific)
Vidhanaarac hchi et al. (2025) –	CNN (transfer learning), Mask R-CNN, YOLOv5	Sri Lankan coconut leaf	90% (early detection), 97% (severity), 95.26%	Strong performance across multiple	Focused only on WCLWD + caterpillar, limited diseases

Early Diagnosis & Severity Assessment		dataset	mAP, 96.87% (caterpillar detection)	tasks	
Wijesinghe et al. (2025) – UAV Multispectral Imaging	UAV multispectral + OBIA + SVM	Coconut leaf dataset (bands B+G+RE+NIR)	79.25%	Effective in multispectral imaging	Low Kappa (0.493), needs molecular/genetic support
Manoharan et al. (2024) – Nutrient Deficiency	RetinaNet, Faster R-CNN, YOLOv5, YOLOv9	5,720 coconut leaf images	YOLOv9: 80% acc., 98.59% precision, 80.37% recall	High precision, real-world application	Limited classes, modest accuracy
Kavithamani & UmaMaheswari (2023) – Whitefly Identification	Drone images + VGG16 (crown) + Custom DCNN	Drone-captured coconut leaves	98.35% acc., 97.32% perf. ratio, 95.71% efficiency	Accurate for pest & disease detection	Only whitefly + a few diseases
Nesarajan et al. (2020) – Coconut Disease Prediction System	SVM + CNN (EfficientNetB0), OpenCV-based monitoring	Android app (field dataset)	SVM: 93.54%, EfficientNetB0: 93.72%	Mobile-ready, real-time	Limited dataset, lacks field trials
Montero et al. (2023) – CNN Classification	2D-CNN, supervised learning	5,017 labeled images	99–100% training, 99.8% testing	Reliable early detection	Possible overfitting, no field test
Marasigan et al. (2024) – Coconut Tree Detection	UAV orthophotos + YOLOv7	Annotated datasets	98% detection, 86.3% localization	Strong detection, validated	Only localization, not disease detection
Iqbal et al. (2021) – Tree Segmentation	Mask R-CNN with ResNet50/101	Aerial imagery dataset	91% mAP, 92% F1, 98% accuracy	Strong in segmentation tasks	Expensive UAV requirement
De Silva et al. (2023) – PCR Detection	Nested PCR (WCLWD palms)	PCR samples	88%	Molecular accuracy	Lab-based, not scalable
Perera et al. (2016) – Hybrid Tolerance Study	Evaluation of SLT vs CRIC65 hybrids	Field survey	—	Found CRIC65 more tolerant	Not ML-based
Ergun (2024) – GoogleNet Classification	GoogleNet CNN + transfer learning	5,798 images, 5 classes	98.24% (outperformed	Strong classification	Needs more variety

n			ResNet 94%)		
Wijethunga et al. (2023) – Crop Disease Mgmt.	CNN + Mask R-CNN + Logistic Regression, MPR	Image dataset	—	Combined disease + soil prediction	No accuracy benchmark

V. CONCLUSION

This systematic review demonstrates that deep learning models, particularly CNN-based architectures, hold strong potential for the early detection and diagnosis of coconut leaf diseases in Sri Lanka's Coconut Triangle. The integration of environmental data such as rainfall, humidity, and temperature has been shown to enhance predictive accuracy and contextual relevance, making models more suitable for region-specific agricultural applications. Nevertheless, the review highlights persistent challenges, including the limited availability of diverse and region-specific datasets, the under-exploration of multi-disease detection frameworks, and the lack of large-scale deployment strategies that address the realities of smallholder farmers.

Future research should focus on building large, standardized, and varietal-specific datasets that reflect the diverse agro-ecological conditions of Sri Lanka. In addition, exploring advanced architectures such as EfficientNet, ResNet, and Vision Transformers can improve detection accuracy while reducing computational costs, making systems more adaptable to mobile and edge devices. Another critical direction involves the development of lightweight, farmer-friendly mobile applications and IoT-based tools that allow real-time, offline disease detection and provide instant, actionable recommendations. Such systems should also incorporate user feedback mechanisms to continuously improve model reliability in real-world settings.

Equally important is the need for field validation and pilot trials to bridge the gap between laboratory experiments and practical agricultural deployment. Without these trials, even highly accurate models may fail to perform under variable lighting, soil, and disease conditions in plantations. Furthermore, the integration of disease forecasting models—combining historical data with real-time climate inputs—can shift the focus from reactive disease control to proactive prevention, enabling farmers to make informed decisions before outbreaks occur.

By addressing these gaps, Sri Lanka's coconut industry can transition towards sustainable, technology-driven disease management systems that not only protect crop yields but also strengthen farmer resilience, ensure long-term agricultural productivity, and safeguard rural livelihoods. Ultimately, this review underscores the importance of aligning academic innovations with practical, scalable, and region-specific solutions that can directly benefit the farming communities most vulnerable to coconut disease outbreaks.

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