REVIEW PAPER

A Comprehensive Review of Deep Learning Techniques for Early Detection of Quick Wilt Disease in Pepper Plants

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Abstract

Black pepper (*Piper nigrum*) is one of the most economically significant spice crops cultivated across tropical regions. Ranks among the world's most economically valuable spice crops, cultivated widely across tropical and subtropical regions. However, its productivity is severely affected by Quick Wilt disease, primarily caused by *Phytophthora capsici*. Yet, crop productivity is severely threatened by Quick Wilt disease, caused primarily by the pathogen *Phytophthora capsici*. Early and accurate detection of this disease remains a major challenge in precision agriculture due to subtle early-stage symptoms and dependence on manual field inspection. Remains a significant challenge in precision agriculture, owing to the subtlety of early-stage symptoms and the continued reliance on labor-intensive manual inspection. In recent years, deep learning techniques have demonstrated promising capabilities in automated plant disease detection using image-based and sensor-driven data. Deep learning has recently emerged as a powerful tool for automated plant disease detection, leveraging both image-based and sensor-driven data sources. This study presents a systematic review of deep learning approaches applied to early detection of Quick Wilt disease in pepper plants. The review follows PRISMA guidelines, with literature retrieved from Scopus and Web of Science databases spanning 2015 to 2026. Relevant peer-reviewed articles were analyzed and categorized by model architecture, dataset characteristics, performance metrics, and deployment strategies. The findings indicate that convolutional neural networks (CNNs) and transfer learning models dominate the field, with reported accuracies exceeding 90% in controlled environments. Achieving accuracies above 90% under controlled conditions. Nonetheless, key limitations persist, including small datasets, insufficient real-field validation, and limited model explainability. This review identifies critical

research gaps and outlines future directions toward robust, scalable, and field-deployable disease detection systems for sustainable pepper cultivation.

Keywords: Quick Wilt Disease, Piper nigrum, Deep Learning, Convolutional Neural Network (CNN), Multimodal Imaging, Early Disease Detection.
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Introduction

Black pepper (*Piper nigrum*) is among the most economically significant spice crops grown across tropical and subtropical regions worldwide. Often referred to as the "King of Spices," it plays a vital role in the agricultural economy of countries such as India, Vietnam, Indonesia, and Brazil. Widely regarded as the "King of Spices," it plays a vital role in the agricultural economies of major producing nations including India, Vietnam, Indonesia, and Brazil. Despite its commercial importance, pepper cultivation faces serious challenges from various fungal and bacterial diseases that substantially reduce both yield and quality. Among these, Quick Wilt disease caused primarily by *Phytophthora capsica* is considered one of the most destructive threats to pepper production.

Quick Wilt disease spreads rapidly under conditions of high humidity and rainfall, triggering root rot, leaf yellowing, stem blackening, and eventual plant collapse. The major difficulty in controlling this disease lies in its subtle early-stage symptoms, which are often visually indistinguishable from nutrient deficiencies or minor environmental stress. A central challenge in managing this disease is that early-stage symptoms are frequently indistinguishable from nutrient deficiencies or mild environmental stress. By the time visible symptoms become apparent, the infection may have already progressed significantly, rendering chemical or agronomic interventions less effective. Consequently, early and accurate detection is essential for minimizing economic losses and ensuring sustainable pepper cultivation.

Traditional disease detection methods rely heavily on manual field inspection and laboratory-based pathogen analysis. These approaches are time-consuming, labor-intensive, and highly dependent on expert knowledge. Conventional disease detection relies on manual field inspection combined with laboratory-based pathogen analysis methods that are time-consuming,

labor-intensive, and heavily dependent on specialized expertise. Moreover, visual assessment by farmers is prone to misdiagnosis, particularly during early infection stages. Recent advances in artificial intelligence, especially deep learning, have opened new avenues for automated and precise plant disease detection.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated considerable success in image-based classification and pattern recognition tasks. Unlike conventional machine learning approaches that require handcrafted feature extraction, CNNs automatically learn hierarchical features directly from raw image data. Learn hierarchical feature representations directly from raw image data without manual engineering. In agricultural applications, deep learning has been widely adopted for leaf disease classification, pest detection, and crop health monitoring. However, many existing studies focus primarily on fully developed disease symptoms and controlled datasets, limiting their effectiveness in real-world field environments, which constrains their practical effectiveness under real-world field conditions.

Furthermore, variations in lighting conditions, background complexity, leaf orientation, and symptom diversity pose significant challenges for reliable disease identification. Recent research suggests that integrating multimodal imaging techniques including RGB, thermal, and hyperspectral imaging can enhance detection capability by capturing both visible and non-visible stress indicators, enabling models to identify physiological changes before overt visual symptoms emerge.

In this context, the present study proposes a deep learning-based framework for the early detection of Quick Wilt disease in black pepper plants. Against this backdrop, this study proposes a deep learning framework for the early detection of Quick Wilt disease in black pepper plants. By leveraging advanced CNN architectures and multimodal imaging data, the proposed approach aims to identify subtle disease patterns at early infection stages, with a focus on improving diagnostic accuracy under real cultivation conditions while ensuring model robustness and practical deployability.

The major contributions of this work include:

1. Development of a lesion-aware deep learning framework for early-stage Quick Wilt detection.
2. Integration of multimodal imaging to enhance symptom recognition capability.
3. Comprehensive performance evaluation using field-acquired datasets.
4. Comparative analysis with established transfer learning models.

By enabling early intervention and precision-based crop management, the proposed system supports sustainable agriculture and improved productivity in pepper cultivation.

Literature review

Recent advancements in deep learning techniques have significantly transformed the field of image analysis and pattern recognition. These models are designed to automatically learn meaningful features from large volumes of data, eliminating the need for manual feature extraction. Advances in deep learning have substantially transformed image analysis and pattern recognition, enabling models to extract meaningful features from large datasets without manual engineering. In agricultural contexts, convolution-based architectures have proven particularly effective in detecting and classifying plant diseases across growth stages. By capturing subtle visual cues such as minor discoloration, texture variations, and structural deformities, these techniques support early and accurate disease diagnosis thereby improving timely decision-making and sustainable crop management.

OpenGenus[1] provides a structured overview of CNN architectures and their significance in deep learning applications. The resource traces the evolution from early networks such as LeNet to more advanced models including AlexNet, VGG, ResNet, Inception, and DenseNet, explaining how innovations such as increased network depth, residual connections, and parallel convolutional blocks have progressively enhanced feature extraction and classification accuracy. This foundational reference is particularly relevant for researchers selecting appropriate architectures for plant disease detection tasks.

Taterwal[2] investigated pepper leaf disease detection using CNNs in combination with traditional machine learning classifiers. The study compared deep learning models against conventional classifiers for recognizing infected leaves from image datasets. CNN-based approaches outperformed traditional methods in feature extraction and classification accuracy, underscoring

the growing importance of deep learning in agricultural diagnostics and pointing to further improvements through expanded datasets and real-time deployment.

Barbedo[3] investigated plant disease identification by focusing specifically on individual lesions and symptomatic spots rather than analyzing the entire leaf. examined plant disease identification through localized lesion and spot analysis, rather than treating the full leaf as the unit of classification. The study demonstrated that focusing on infected regions improved classification accuracy compared to whole-leaf approaches, highlighting the value of region-specific analysis in plant pathology.

E. C. Tool[4] et al. conducted a comparative study on fine-tuning pre-trained deep learning models

for plant disease detection. Evaluating multiple CNN architectures under transfer learning settings, the authors found that fine-tuned networks significantly outperformed models trained from scratch, particularly when labeled data were scarce. The study concluded that model selection and hyperparameter tuning are critical determinants of classification performance.

J. G. A. Barbedo[5] investigated how dataset size and variability influence the effectiveness of deep learning and transfer learning approaches in plant disease classification. The findings highlighted that both the volume and diversity of training data play a critical role in enhancing model generalization. Although transfer learning provided noticeable improvements when training data were limited, incorporating greater variability within the dataset significantly strengthened model robustness. The study ultimately emphasized the importance of expanding and diversifying datasets to support dependable real-world agricultural applications.

R. Thangaraj[6] et al. developed an automated framework for classifying tomato leaf diseases using a transfer learning-based deep convolutional neural network. By utilizing pre-trained architectures, the system improved feature extraction efficiency and reduced training complexity. Experimental validation demonstrated strong classification performance, reinforcing the suitability of transfer learning techniques for targeted crop disease identification.

M. H. Saleem[7] et al. conducted a comprehensive comparison of multiple convolutional neural network architectures alongside different deep learning optimization algorithms for plant disease recognition. Their systematic assessment revealed that the choice of optimizer substantially

affects convergence behavior and overall predictive accuracy. The results underscored the necessity of carefully selecting and tuning optimization strategies to achieve superior model performance.

R. Thangaraj[8] et al. team introduced an automated approach for detecting tomato leaf diseases based on a transfer learning-driven deep convolutional neural network. By incorporating pre-trained network architectures, the proposed framework strengthened feature representation while reducing the need for extensive training from scratch. The experimental results demonstrated strong predictive performance, highlighting the practicality of transfer learning methods for accurate and crop-focused disease diagnosis.

M. H. Saleem[9] et al. carried out a detailed comparative study of multiple convolutional neural network models in combination with different optimization algorithms for plant disease recognition. Their analysis explored how varying optimization techniques impact model learning dynamics. The findings revealed that optimizer choice plays a decisive role in determining convergence efficiency and overall classification accuracy, emphasizing the importance of strategic hyperparameter tuning to achieve optimal model outcomes.

A. Sagar[10] et al. investigated the use of transfer learning techniques for plant disease identification. Their findings indicated that convolutional neural networks pre-trained on large-scale datasets can be successfully adapted to agricultural image data, even when only a limited number of labeled samples are available. The study emphasized transfer learning as a viable and resource-efficient strategy, particularly in agricultural settings where collecting extensive annotated datasets is often challenging.

R. I. Hasan[11] et al. conducted an extensive review examining the role of deep learning methods in plant disease diagnosis. The authors evaluated a range of convolutional neural network architectures, publicly available datasets, and commonly adopted performance metrics across prior studies. Their analysis highlighted persistent issues, including class imbalance, variations in environmental conditions, and constraints related to real-time implementation. Additionally, the review provided valuable insights into potential research opportunities aimed at improving robustness and practical deployment of disease detection systems.

S. M. Hassan[12] et al. introduced a transfer learning framework built upon convolutional neural networks for the detection of plant leaf diseases. The proposed model achieved robust classification results across a wide range of disease categories. The authors underscored the importance of leveraging feature representations learned from large-scale pre-trained networks, noting that such reuse significantly enhances predictive accuracy while minimizing computational demands, particularly in resource-constrained environments.

A. Devaraj[13] et al. designed a plant disease detection system integrating conventional image processing methods with machine learning classifiers. Their methodology involved sequential preprocessing, image segmentation, and handcrafted feature extraction prior to the classification stage. Although the system delivered satisfactory performance, it relied heavily on manual feature engineering, thereby illustrating the comparative advantage of deep learning approaches that enable automated and hierarchical feature learning.

S. K. Upadhyay[14] et al. concentrated on the early detection of brown spot disease in paddy crops by integrating image processing techniques with deep learning methodologies. Their work highlighted the importance of identifying disease symptoms at an initial stage to mitigate potential yield losses. A convolutional neural network framework was designed and trained using paddy leaf images captured under real-field cultivation environments. The experimental findings revealed that deep learning models are capable of detecting subtle early-stage visual patterns; however, the authors recommended further large-scale validation across varied environmental and geographical conditions to ensure broader applicability.

M. Hasan[15] et al. introduced a transfer learning-driven approach for tomato leaf disease identification within precision agriculture systems. By adopting pre-trained convolutional architectures, the proposed model improved feature extraction efficiency while significantly reducing computational training requirements. The empirical results demonstrated high classification performance, reinforcing the suitability of transfer learning techniques, particularly in scenarios where agricultural datasets are relatively small or insufficiently labeled.

L. Li[16] et al. presented an extensive survey of deep learning methodologies employed for plant disease detection and classification. Their review offered a structured analysis of various convolutional neural network architectures, optimization strategies, and dataset-related constraints encountered in prior studies. The authors identified persistent challenges, including class imbalance and variability between laboratory and field conditions. They further emphasized the necessity of developing lightweight architectures capable of real-time deployment to enhance practical applicability in precision agriculture.

M. Arsenovic[17] et al. examined critical shortcomings in existing deep learning-driven plant disease diagnostic systems. Their investigation highlighted concerns such as dataset bias, model overfitting, and insufficient generalization to real-world agricultural environments. To address these issues, the study proposed methodological improvements focused on increasing dataset diversity and implementing more rigorous validation frameworks to strengthen model robustness and reliability.

A. S. Paymode[18] et al. explored the application of transfer learning using VGG-based convolutional neural networks for multi-crop leaf disease recognition. Their findings demonstrated enhanced classification performance across various crop species, suggesting that feature representations derived from pre-trained models can effectively transfer across different agricultural domains. The study reinforced the potential of transfer learning to facilitate scalable and adaptable plant disease detection systems.

A. Kaya[19] et al. examined various transfer learning strategies applied to plant classification problems. Their work involved a comparative assessment of fine-tuning techniques across multiple deep neural network architectures. The results indicated that selectively freezing certain network layers, combined with systematic hyperparameter optimization, can substantially improve classification accuracy and overall model efficiency.

G. Geetharamani[20] et al. proposed a nine-layer deep convolutional neural network tailored specifically for plant leaf disease recognition. In contrast to transfer learning-based methods, their model was trained entirely from the ground up. Despite the absence of pre-trained weights, the architecture delivered encouraging performance, demonstrating that carefully structured custom CNN models can compete effectively with transfer learning approaches when sufficient training data are available.

R. Barth[21] et al. introduced a synthetic bootstrapping strategy aimed at enhancing semantic segmentation of plant components. By generating artificial training samples, the study strengthened the learning capacity of convolutional networks in data-scarce scenarios. The findings confirmed that synthetic data augmentation can effectively mitigate the limitations associated with insufficient annotated datasets.

A. S. Kini[22] et al. presented a comprehensive review of image processing and deep learning methodologies for plant leaf disease detection. Their comparative analysis between traditional image-based techniques and modern convolutional neural network frameworks concluded that automated feature extraction through deep learning provides superior accuracy, adaptability, and scalability for large-scale agricultural applications.

B. Rajesh[23] et al. employed decision tree-based classification techniques for identifying leaf diseases. Their methodology was grounded in the extraction of handcrafted visual features from leaf imagery prior to classification. Although the model achieved satisfactory predictive performance, the authors recognized inherent constraints associated with conventional machine learning algorithms, particularly when compared to the automated feature learning and higher scalability offered by deep learning frameworks.

S. Coulibaly[24] implemented deep neural networks enhanced through transfer learning for the detection of diseases in millet crops. By fine-tuning pre-trained convolutional neural network architectures on millet-specific datasets, the study reported notable improvements in classification accuracy. The findings further reinforced the flexibility and cross-crop adaptability of transfer learning approaches in agricultural disease diagnostics.

M. Vilasini[25] explored convolutional neural network-based classification of Indian leaf species using images captured via smartphones. The research underscored the feasibility of mobile-enabled disease detection systems, particularly in terms of accessibility and real-world deployment. The study emphasized that such portable solutions hold significant promise for supporting farmers in rural and resource-limited agricultural environments.

J. Liu[26] et al. presented a comprehensive review of deep learning methodologies for plant disease and pest identification. Their analysis encompassed both image classification models and object detection frameworks, highlighting an emerging transition toward real-time implementations and edge-computing-based solutions. The study emphasized the growing demand for lightweight and deployable systems capable of operating efficiently under field conditions.

A. Fuentes[27] et al. designed a robust deep learning-based detection system for real-time recognition of tomato diseases and pests. By integrating advanced object detection techniques, the proposed model was capable of simultaneously identifying multiple disease categories within a single image. Experimental evaluations demonstrated reliable performance in real agricultural environments, even under challenging and visually complex background conditions.

K. Yang[28] et al. introduced a deep learning-driven framework for accurate leaf segmentation and subsequent classification in cluttered field settings. Their work addressed the difficulties associated with complex backgrounds and occlusions commonly encountered in outdoor agricultural imagery. The findings revealed that precise segmentation significantly improves classification outcomes by isolating relevant leaf regions from surrounding noise.

J. Chen[29] et al. proposed a stacking ensemble-based deep learning architecture for plant disease recognition. By combining predictions from multiple neural network models, the ensemble approach enhanced overall predictive stability and minimized misclassification errors. The results indicated that model fusion strategies can effectively improve robustness and reliability in agricultural disease detection systems.

Y. A. Nanehkaran[30] et al. investigated plant leaf disease recognition through the combined use of computer vision techniques and deep learning models. Their framework integrated image preprocessing, segmentation procedures, and convolutional neural network-based classification to enhance diagnostic accuracy. The study demonstrated that a structured processing pipeline significantly improves the reliability of automated disease identification systems.

S. S. Chouhan[31] et al. applied optimization-based algorithms to improve leaf segmentation performance. Although the primary focus of their research was segmentation rather than direct classification, the findings emphasized that precise leaf extraction forms a critical foundation for accurate disease detection and subsequent analysis.

R. Khajuria[32] et al. provided a comprehensive survey of artificial neural network-driven methods for leaf disease diagnosis. The review outlined traditional ANN-based approaches and discussed the progressive shift toward deeper convolutional neural network architectures, reflecting the evolving landscape of intelligent agricultural systems.

S. S. Chouhan[33] et al.introduced a publicly accessible leaf image dataset intended to support plant disease research. This repository was developed to enable standardized benchmarking and facilitate comparative evaluation of various machine learning and deep learning models within the research community.

S. S. Chouhan[34] et al. proposed a radial basis function (RBF) neural network-based framework for mango leaf disease segmentation. The web-enabled architecture allowed remote monitoring and analysis, representing an early step toward the implementation of digital and network-integrated agricultural solutions.

S. S. Chouhan[35] et al. conducted a broad survey on computer vision applications in plant pathology. Their review encompassed segmentation, classification, and object detection methodologies, highlighting the accelerating adoption of deep learning technologies in modern agricultural diagnostics.

Research Gap

Although significant progress has been made in applying deep learning techniques for plant disease detection, several critical limitations remain unaddressed, particularly in the context of Quick Wilt disease in black pepper (Piper nigrum).

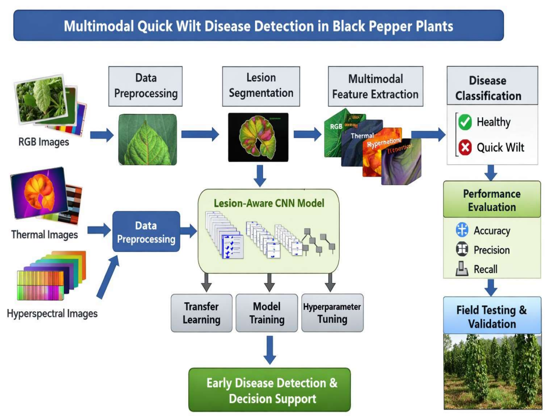
1. Existing deep learning models primarily focus on fully developed plant disease symptoms rather than early-stage detection.
2. Most studies rely only on RGB images, limiting robustness under real-field environmental variability.
3. Lesion-level and localized symptom analysis remains insufficiently explored in black pepper disease detection.
4. Insufficient validation under real-field conditions, along with limited dataset variability, constrains the generalization performance of existing disease detection models.
5. A dedicated multimodal deep learning framework for early detection of Quick Wilt disease in black pepper is still lacking.

Research Objective

Based on the identified gaps, the following are the core objectives of this study

1. To design and implement a robust deep learning-driven framework for the early-stage detection of Quick Wilt disease caused by Phytophthora capsici in black pepper (Piper nigrum) plants.
2. To integrate and evaluate multimodal imaging data (RGB, thermal, and hyperspectral) for enhancing disease detection accuracy under real-field environmental conditions.
3. To design and implement a lesion-aware convolutional neural network model that focuses on localized symptomatic regions rather than whole-leaf classification.
4. To perform comprehensive performance evaluation and comparative analysis using transfer learning architectures, cross-validation techniques, and field-acquired datasets to ensure robustness and generalization.

Methodology



1. Data Collection

RGB, thermal, and hyperspectral images of black pepper leaves are collected from both healthy and Quick Wilt–infected plants. The data is gathered under real field conditions to ensure practical relevance. Multiple samples are captured at different growth stages and lighting conditions. This ensures diversity and improves model generalization.

2. Data Preprocessing

All collected images are resized to a standard dimension to ensure model compatibility. Noise reduction and contrast enhancement are performed to improve visual quality. In hyperspectral datasets, non-essential spectral bands are eliminated to reduce redundancy. Data normalization is applied to ensure consistency across all input modalities.

3. Lesion Segmentation

Segmentation techniques are used to isolate the infected regions from the leaf background. This step helps the model focus only on disease-affected areas. Deep learning–based segmentation methods such as U-Net can be applied for accurate region extraction. The segmented output improves feature learning efficiency.

4. Feature Extraction

Important features such as color, texture, and shape are extracted from RGB images. Thermal images provide temperature distribution patterns related to plant stress. Hyperspectral images contribute spectral signatures indicating biochemical changes. Deep CNN layers automatically learn high-level discriminative features from all modalities.

5. Multimodal Feature Fusion

Extracted features from all three modalities are combined using fusion techniques. This integration captures complementary information from visual, thermal, and spectral domains. Feature fusion enhances robustness and reduces misclassification. It creates a unified representation for accurate disease detection.

6. Model Training

A lesion-aware Convolutional Neural Network (CNN) model is developed for classification. Transfer learning can be applied to improve performance with limited data. The model parameters are optimized using backpropagation and appropriate loss functions. Hyperparameter tuning is performed to achieve optimal accuracy.

7. Classification

The trained model classifies leaf samples into healthy or Quick Wilt infected categories. A softmax activation function is used in the final layer for probability prediction. The model outputs confidence scores for each class. This enables reliable and automated decision-making.

8. Performance Evaluation

The model performance is evaluated using accuracy, precision, recall, and F1-score. A confusion matrix is generated to analyze classification results. Cross-validation techniques ensure robustness and reliability. The evaluation confirms the effectiveness of the proposed framework.

9. Field Validation

The trained system is deployed in real plantation environments for testing. Its ability to detect disease under natural conditions is examined. Practical feasibility and response time are assessed. This step ensures the system is suitable for real-world agricultural applications.

Conclusion

This study proposed a deep learning–based framework for the early detection of Quick Wilt disease in black pepper (*Piper nigrum*). The integration of RGB, thermal, and hyperspectral imaging improved the identification of subtle early-stage symptoms. A lesion-aware CNN model enhanced classification accuracy by focusing on infected regions rather than whole-leaf analysis. Transfer learning techniques further strengthened performance, particularly with limited datasets. Comprehensive evaluation confirmed robustness through cross-validation and field-based testing. The findings demonstrate the importance of multimodal feature fusion for reliable disease detection. However, challenges such as dataset scalability and real-time deployment

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