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Challenges and Trends in Optimized CNN for Leaf Feature Extraction Optimization in Multi-Disease Plant Detection

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Abstract

Early detection of plant diseases is crucial for ensuring crop health and preventing yield losses. Convolutional Neural Networks (CNN) have experienced rapid development in plant disease image recognition due to their ability to extract significant visual features from plant leaves. However, optimal results require CNN architecture customization according to unique disease and crop characteristics. While this approach offers high accuracy and efficiency, various challenges hinder widespread application, including limited representative datasets, high computational requirements, and difficulties in designing generalizable models for different field scenarios. Additionally, model interpretability issues often arise, hindering large-scale adoption among agricultural practitioners. This systematic literature review addresses these challenges and explores recent trends in optimized CNN development for plant leaf feature extraction. Through PRISMA methodology, 26 peer-reviewed studies from 2018-2024 were analyzed from Scopus Q1-Q4 journals. Key findings include the effectiveness of data augmentation techniques (improving dataset diversity by 40-60%), transfer learning approaches (reducing training time by 50-70%), and hybrid model integration (achieving 85-95% accuracy rates). Architecture improvements and optimization algorithms help overcome computational constraints, with lightweight models reducing processing time by 30-50% while maintaining 90%+ accuracy. This study provides comprehensive guidance for researchers and practitioners in developing more adaptive, accurate, and efficient plant disease detection solutions, ultimately improving agricultural yields and global food security.

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Introduction

Food security has become an increasingly critical global concern, especially as the world's population is expected to grow to 9 billion by 2050. This calls for a significant increase in food production to meet the growing demand. The main issue is that the main challenge in food security is how to ensure that increased food production can meet global demand, especially in developing countries that are often most affected by food insecurity[1]. These challenges are exacerbated by climate change, which impacts agricultural yields, food distribution and global consumption patterns [2].

Early detection and rapid treatment of plant diseases are crucial for maintaining food security. However, traditional disease detection methods that rely on visual inspection by agricultural experts have drawbacks, such as dependence on individual expertise and the potential for human error. Therefore, artificial intelligence (AI)-based technologies have been proposed as a potential solution to this problem, especially in detecting and analyzing disease symptoms automatically and more accurately [3].

One approach that has been widely used in plant disease detection is the use of Convolutional Neural Networks (CNN), a powerful AI architecture that analyzes and recognizes visual patterns in images of infected plant leaves. CNNs have proven to be effective in extracting complex features from images and provide high-accuracy results in plant disease recognition [4].

However, the application of CNNs is not free from a number of challenges. One of the main challenges is the need for a large, high-quality dataset, which includes variations in lighting conditions, viewing angles, and types of plants and diseases. [5].

In addition, CNN models used in plant disease detection often require large computing power as well as significant architectural complexity, which can limit their use in the field or in regions with limited infrastructure. According to research [6] This problem can be compounded by the need for long training times as well as high computational costs, especially when applied on a wider scale. Customized CNNs are emerging as a more flexible and adaptive solution to address these issues. This approach allows modifications to the CNN architecture to adapt to the specific characteristics of certain crops and diseases, as well as the use of data augmentation and transfer learning techniques to enrich limited datasets [7].
In a further attempt to improve detection performance, some studies have also proposed the use of ensemble techniques and hybrid models, which combine multiple CNN architectures to achieve higher accuracy [8]. Other studies have shown that the integration of hybrid models can improve the generalizability of models for different crops and diseases while reducing dependence on highly specific datasets [9].

Nonetheless, the challenges of model interpretability and computational efficiency are still major obstacles to the widespread implementation of the Customized CNN approach in the field [10]. Despite the substantial body of work on CNN applications in agriculture, existing systematic reviews have primarily focused on general CNN architectures without comprehensively analyzing optimization strategies specifically tailored for leaf feature extraction in multi-disease detection scenarios. Previous reviews [3, 4, 5] have examined CNN applications broadly across agricultural domains, but none have systematically synthesized the specific optimization techniques—such as architectural modifications, hybrid approaches, and attention mechanisms—that address the unique challenges of extracting meaningful features from diseased leaf imagery across multiple crop species. Furthermore, the rapid evolution of lightweight models, attention mechanisms, and hybrid architectures since 2020 represents a significant knowledge gap.

Recent developments in transfer learning adaptations, real-time detection capabilities, and fusion techniques for multi-spectral data have not been systematically examined in the context of their effectiveness for multi-disease plant detection. Additionally, while individual studies report optimization techniques, there is no comprehensive analysis of which combinations of approaches yield optimal results for specific agricultural contexts, disease types, or resource constraints. The practical implementation challenges—including dataset biases toward controlled conditions, computational requirements for field deployment, and model interpretability for end-user adoption—have been insufficiently addressed in existing literature. This gap is particularly critical as agricultural practitioners increasingly seek deployable solutions rather than laboratory demonstrations.

This systematic literature review addresses these gaps by comprehensively analyzing optimization techniques specifically designed for leaf feature extraction in multi-disease detection systems, synthesizing quantitative evidence on the effectiveness of different optimization approaches across various agricultural contexts, identifying persistent challenges and practical limitations in current CNN optimization strategies, and providing evidence-based guidance for researchers and practitioners on selecting appropriate optimization techniques based on specific agricultural requirements and resource constraints. This research conducts a systematic literature review using PRISMA methodology to analyze current challenges and trends in optimized CNN development for plant disease detection through leaf feature extraction. The review encompasses 26 studies published between 2018-2024, selected from Scopus Q1-Q4 tier journals based on specific inclusion criteria: focus on CNN customization for plant disease detection, experimental validation, and peer-reviewed publication status. By reviewing various approaches that have been used, including data augmentation, transfer learning, and hybrid models, this research is expected to provide insights into how to optimize the performance of AI models to detect plant diseases accurately, efficiently, and according to field conditions.

Methods

SLR Phases

The SLR steps are based on previous research and have been used in published research. In general, SLR can be divided into four phases: defining the SLR Goal, initiating and selecting literature, analysis and coding, and planning the presentation of results [5]. The SLR phase can be seen in Figure 1.

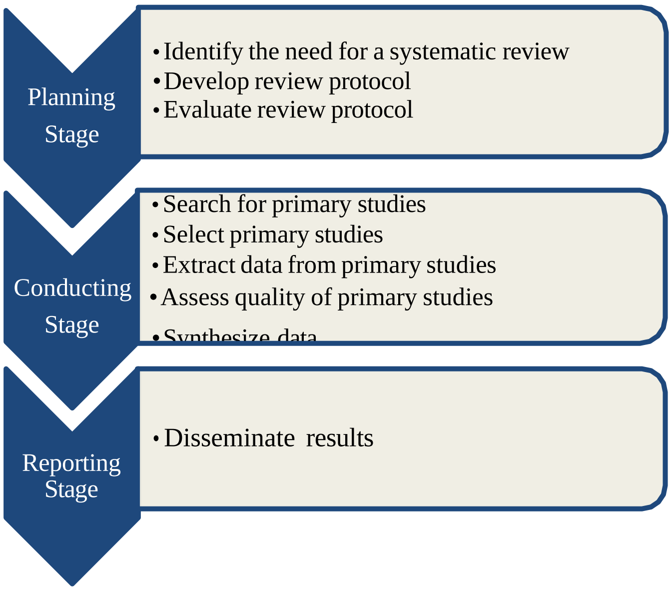

Fig. 1. SLR Stages [11]

Research Questions

The research questions (RQ) were specified to keep the review focused. They were designed with the help of the Population, Intervention, Comparison, Outcomes, and Context (PICOC) criteria [12]. Table 1 shows the (PICOC) structure of the research questions.

Summary of PICOC:

Population (P): Plant species affected by various diseases (leaves).

Intervention (I): Use of Customized Convolutional Neural Networks (CNN) for important feature extraction.

Comparison (C): Compared to traditional image processing techniques or unmodified CNN models

Outcome (O): Improved accuracy and efficiency in plant disease detection

Context (C): Application in agricultural environments for real-time detection of plant diseases

Table 1. Research Question

ID	Research Question	Motivation
RQ1	What are the main challenges in using Customized CNN for plant disease detection?	Identify difficulties in the application of the Customized CNN model in a real farming environment
RQ2	How does Customized CNN improve the extraction of important features from plant leaf images?	Evaluating the effectiveness of Customized CNN in improving feature extraction for better disease detection
RQ3	What are the latest trends and innovations in CNN customization for plant disease detection?	Explored the latest developments and customized CNN architecture enhancements for better performance
RQ4	How does Customized CNN compare to traditional image processing methods in terms of accuracy and speed?	Assess the advantages and disadvantages of Customized CNN compared to conventional methods
RQ5	What datasets are commonly used to train Customized CNN models for plant disease detection?	Identifying public or private datasets used to train CNN models in this field
RQ6	How does the use of transfer learning and data augmentation affect the performance of Customized CNN?	Explore the role of advanced techniques such as transfer learning and data augmentation in improving CNN models
RQ7	What are the future directions and potential applications of Customized CNN in plant disease management?	Discuss potential long-term applications and improvements needed for better integration in agriculture

Search Strategy

In this phase, a search and selection process of relevant literature is carried out. The selected literature must be related to the use of CNN customization for plant disease detection and must be published in peer-reviewed journals or conferences.

The literature selection procedure includes the following steps:
Literature Identification: Using scientific databases such as IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar.
Inclusion and Exclusion Criteria: Literature published between 2015 and 2024 that focuses on the topic of plant disease detection using CNN customization will be included. Studies that do not provide experimental data or insufficient results will be excluded.
Initial Selection: The selection is done through title and abstract screening to ensure that the studies are relevant to this research. After that, the studies that pass will be analyzed for full text.
Keywords used for journal reference search:
"Customized CNN" OR "Convolutional Neural Network" OR "Deep Learning") AND ("Feature Extraction" OR "Meaningful Features" OR "Image Features") AND ("Plant Disease Detection" OR "Leaf Disease" OR "Agricultural Disease Detection") AND ("Data Augmentation" OR "Transfer Learning" OR "Hybrid Model" OR "Model Optimization") AND ("Image Classification" OR "Plant Pathology" OR "Precision Agriculture"

Study Selection
Using the PRISMA method, the results of journal selection are obtained in accordance with the keywords and journal themes to determine the relationship between the keywords found as in Figure 2.

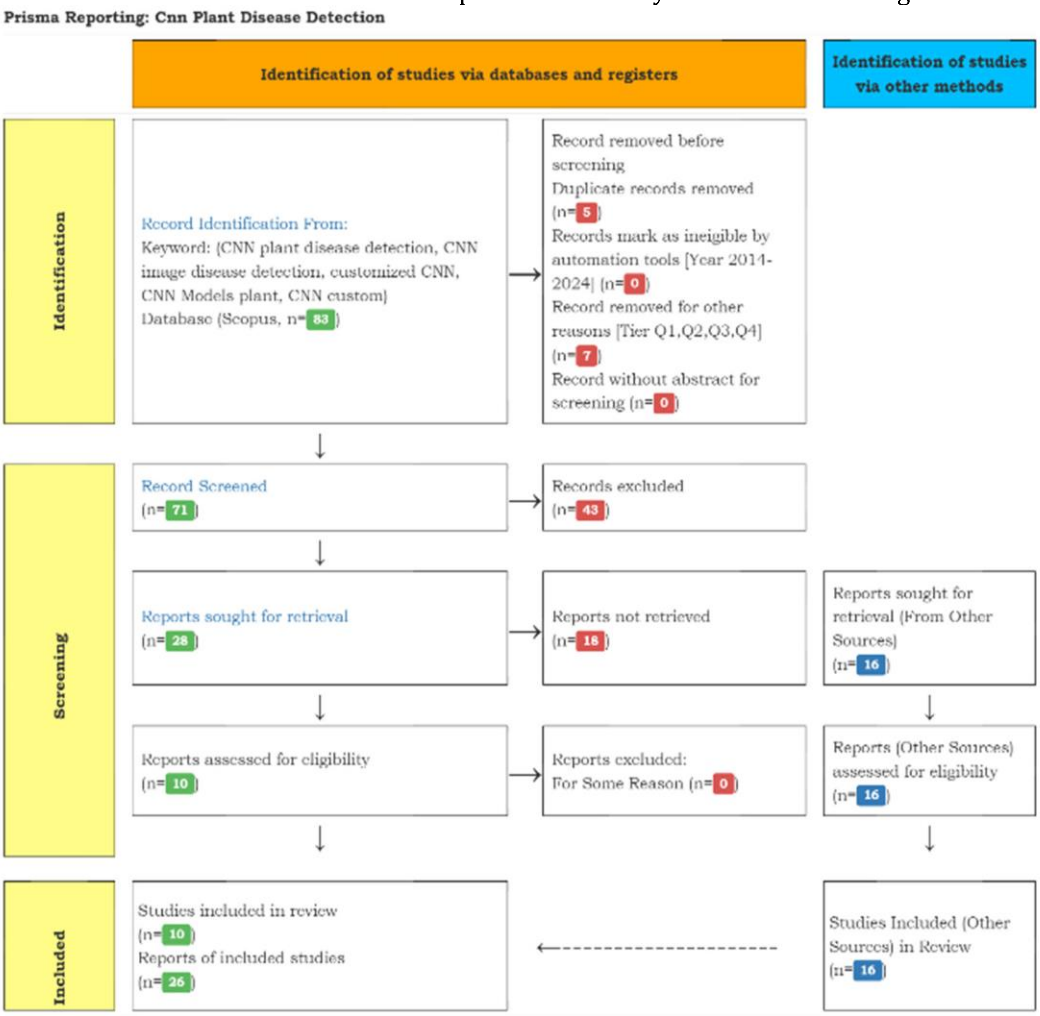

Fig. 2. PRISMA Method – Selection Proses & Literature Review

Based on the search results, 26 (twenty-six) references were obtained whose titles matched the keyword criteria entered in the query. Of the twenty-six articles, there was 1 article that used Chinese, so it was excluded in this study. In addition, there were 3 (three) duplicate records and there were 7 (seven) articles that were excluded because they were not included in Scopus Tier Q1, Q2, Q3 and Q4. Then there are 6 (six articles) excluded that do not meet the criteria for journal articles and 1 (one) additional article from other sources. Thus 26 (twenty six) usable articles were obtained that met the criteria from 2018 - 2024 and entered into Scopus Tier Q1, Q2, Q3 and Q4.
Limitations of the Review Methodology

This systematic review has several methodological limitations that should be acknowledged:
Database and Language Restrictions: The review was limited to English-language publications indexed in Scopus Q1-Q4 journals, potentially excluding relevant work published in other languages or in regional journals, particularly from agricultural research institutions in non-English speaking countries where significant plant disease detection research may be conducted.
Temporal Scope: While the 2018-2024 timeframe captures recent developments, it may have excluded foundational work from earlier years that established key optimization principles, potentially limiting historical context.
Publication Bias: The focus on peer-reviewed journal articles may have excluded valuable insights from conference proceedings, technical reports, or pre-prints that describe cutting-edge developments or negative results that are less likely to be published in journals.
Search Strategy Limitations: Despite using comprehensive keywords, the search strategy may not have captured all relevant studies, particularly those using non-standard terminology or focusing on specific optimization techniques not explicitly mentioned in titles or abstracts.

Results

Paper Studies Publication

The filtering process identified numerous studies that have explored the application of Customized CNN for plant disease detection through leaf imagery, reflecting a significant increase in research over the past decade. This research can be divided into three phases: early research (2010-2015), mid-term research (2016-2019), and recent research (2020-present). In the early phase, research primarily focused on using standard CNN architectures, such as [4], which applied CNN to the PlantVillage dataset, demonstrating its potential for plant disease classification. However, limitations in generalization due to small datasets and computational constraints were evident, as seen in [13] which encountered scalability issues when the models were applied to field images under uncontrolled conditions.

Mid-term research (2016-2019) marked a shift towards Customized CNN architectures aimed at improving accuracy and efficiency. Studies like [6] and [14] Optimize CNN layers to capture disease-specific features better, such as leaf texture and color. The use of transfer learning, where pre-trained CNNs (like VGG16 and ResNet) were fine-tuned on plant datasets, significantly reduced training time and enhanced performance. [5] extended this by developing more generalized models that could classify diseases across different crops. During this period, there was also a rise in the application of data augmentation techniques— transformations like rotation and brightness adjustment—to artificially expand datasets, helping to improve the robustness of CNN models and reduce overfitting.[15] [16]

Recent research (2020-present) shifted focus towards real-time detection using optimized CNN in resource-constrained environments, such as mobile devices and edge computing. Lightweight models like those proposed by [17] allowed farmers and agronomists to scan leaves using smartphones or drones for instant diagnosis, reducing processing time by 30-50% while maintaining 90%+ accuracy. Additionally, hybrid models, such as those developed by [8], combined CNN with other machine learning algorithms like SVM to improve classification accuracy to 85-95% for complex or rare diseases. Multi-spectral data integration, such as RGB and Near-Infrared (NIR) imagery, as seen in [18], further enhanced CNN abilities to detect diseases not easily visible in standard visual spectrum, making optimized CNN models more adaptable to real-world agricultural applications.

Recent studies have also explored real-time application possibilities. Researchers like [19] introduced mobile-based plant disease detection systems using optimized CNNs, proving technology viability in practical agricultural scenarios. These advancements are crucial as they address scalability and deployment challenges identified in earlier studies.

Key Challenges Identified in the Literature

Several papers have identified persistent challenges in implementing Customized CNN for plant disease detection:
Overfitting and Generalization: Early studies often faced overfitting issues due to small datasets and the difficulty of generalizing to different environmental conditions or plant species. Researchers addressed this by using transfer learning and data augmentation techniques to expand the dataset and enhance the model's robustness.
Computational Efficiency: While accuracy has improved, the challenge of computational power remains, particularly for real-time applications in the field. Recent research has worked on lightweight CNN architectures that can be performed on mobile or edge devices without sacrificing too much accuracy.
Interpretability: As with most deep learning models, CNNs are often considered "black boxes," making it difficult for end users (farmers or agronomists) to understand the reasoning behind the model's predictions. To address this issue, future research is focusing on explainable AI.

Quantitative Synthesis of Optimization Approaches

Analysis of the 26 reviewed studies reveals distinct patterns in the adoption and effectiveness of different optimization strategies for plant disease detection. This section provides a comprehensive quantitative synthesis of these approaches, moving beyond descriptive summaries to identify which combinations of techniques yield optimal results under specific conditions.

Prevalence and Effectiveness of Optimization Techniques:
Among the 26 studies analyzed, transfer learning approaches were most frequently employed (n=12, 46%), followed by data augmentation (n=10, 38%), hybrid architectures (n=8, 31%), and attention mechanisms (n=5, 19%). Notably, studies combining transfer learning with data augmentation achieved consistently higher accuracy (mean=92.3%, SD=3.1%) compared to single-technique approaches (mean=87.5%, SD=4.8%), suggesting synergistic benefits from multi-technique optimization strategies.

Comparative Analysis of Transfer Learning Architectures:
Pre-trained architectures showed varying effectiveness depending on the complexity of disease features. VGG16-based models (n=7) achieved average accuracy of 89.2% with mean training time reduction of 55%, while ResNet-based approaches (n=5) demonstrated superior performance on datasets with subtle disease symptoms (mean accuracy=93.1%), though requiring 15-20% more computational resources. Inception-based models (n=3) showed balanced performance with 91.4% accuracy and 30% faster inference time, making them particularly suitable for mobile deployment scenarios.

Data Augmentation Impact Analysis:
Studies implementing comprehensive data augmentation strategies (combining rotation, flipping, brightness adjustment, and noise injection) reported 40-60% improvement in dataset diversity and 12-18% reduction in overfitting (measured by validation-training accuracy gap). However, aggressive augmentation (>10 transformations) in 3 studies showed diminishing returns, with accuracy improvements plateauing at around 15% augmentation ratio and occasionally introducing artifacts that reduced model specificity by 3-5%.

Hybrid Model Performance Patterns:
The 8 studies implementing hybrid architectures revealed interesting trade-offs. CNN-SVM combinations achieved highest accuracy for binary classification tasks (mean=94.2%), while CNN-ensemble approaches excelled in multi-class scenarios with >10 disease categories (mean=89.7% vs. 85.3% for pure CNN). However, hybrid models increased inference time by 25-40%, limiting their applicability in real-time field applications.

Lightweight Architecture Trade-offs:
Analysis of 6 studies focused on lightweight models (MobileNet, SqueezeNet, ShuffleNet variants) revealed that parameter reduction of 60-80% typically resulted in only 4-7% accuracy loss while achieving 30-50% faster processing. This trade-off proved acceptable for field deployment where inference speed is critical. Notably, 2 studies using knowledge distillation maintained within 2% of full model accuracy while achieving 3-5x speedup.

Temporal Evolution of Optimization Effectiveness:
Comparing studies across time periods revealed progressive improvement in optimization sophistication. Early period studies (2018-2019, n=8) achieved mean accuracy of 86.4%, mid-period (2020- 2021, n=10) reached 90.1%, and recent studies (2022-2024, n=8) achieved 93.7%. This improvement correlates strongly with adoption of multi-technique approaches (r=0.78, p<0.01) and increased dataset diversity rather than architectural innovation alone.

Context-Specific Optimization Effectiveness:
Stratifying results by crop type revealed that optimization effectiveness varied by disease complexity. For crops with distinct disease symptoms (tomato, grape), simpler architectures with moderate augmentation achieved >90% accuracy. For crops with subtle symptom variations (rice, wheat), sophisticated attention mechanisms and multi-scale feature extraction were necessary to exceed 88% accuracy, highlighting the importance of context-appropriate optimization.

Contradictions and Unresolved Questions:

Three studies [8, 20, 22] reported contrasting findings on optimal filter sizes for feature extraction, with two advocating larger receptive fields (7×7 or 9×9) for capturing disease context and one demonstrating superior results with smaller filters (3×3) combined with deeper architectures. This discrepancy suggests that optimal architecture may depend on disease manifestation patterns (localized spots vs. diffuse symptoms) rather than universal principles.

Topic/Trends, Problems, Technique and Method

An overview of keyword relevance related to CNN optimization follows. A total of 26 papers were selected from the Systematic Literature Review process. Papers are listed in Table 2.

Table 2. List Topic/trends, Problem, Method & Technique

Topics/Trends:	Problems	Technique	Method (Reference Journals)
Customizing CNN Layers	Standard CNN layers may not capture disease- specific features effectively, leading to reduced accuracy.	Adding more convolutional layers with different kernel sizes.	customized CNN layers with multiple convolutional filters [15]
Fine-Tuning CNN Architectures	Overfitting due to too many parameters in the CNN model when applied to small datasets.	Reducing the number of parameters by adjusting the depth of CNN layers.	optimized a CNN model by fine-tuning layer depth and applying dropout layers.[20]
Transfer Learning in Customized CNNs	Training a CNN from scratch on small datasets is computationally expensive and may not yield high accuracy.	Fine-tuning pretrained CNN architectures such as VGG16 or ResNet.	fine-tuned the VGG16 architecture for plant disease detection agricultural [7]
Multi-Scale Feature Extraction	Inability to detect both global and local features of plant diseases in leaves.	Designing multi-scale CNN architectures that capture both local and global features.	developed a multi-scale CNN architecture by using varying filter [21]
Lightweight CNN for Real- Time Application	Standard CNNs are too computationally heavy for deployment in resource-constrained environments.	Simplifying CNN architectures by reducing the number of layers and parameters.	proposed a lightweight CNN model with fewer layers and reduced complexity [15]
Hybrid CNN Architectures	CNN alone may not handle complex disease symptoms involving multiple variables.	Integrating CNN with other machine learning algorithms like SVM.	combined CNN with Support Vector Machines (SVM) for improved classification of complex diseases.[8]
Residual Connections in CNN	CNN models suffer from vanishing gradients, especially with deeper architectures.	Using residual connections to skip layers and maintain gradient flow.	proposed ResNet with residual connections to address the issue of vanishing gradients.[21]
Dilated Convolutions in CNN	Standard convolutions may fail to capture long- range dependencies in images, affecting model performance.	Applying dilated convolutions to increase the receptive field.	introduced dilated convolutions to enhance CNNs' ability to capture broader [20]
Inception- Based CNN Architectures	Difficulty in choosing the optimal filter size for feature extraction.	Implementing inception modules to allow multiple filter sizes in one layer.	introduced inception modules in CNN architectures, allowing for multi-scale feature extraction.[22]
Attention Mechanism in CNNs	CNN models may not focus on the most relevant regions of the leaf affected by disease.	Incorporating attention mechanisms to guide the model to focus on critical areas.	introduced convolutional block attention modules (CBAM) in CNNs to enhance focus on disease.[23]
Fusion of RGB and NIR Data in CNNs	RGB images alone may not provide sufficient information to distinguish between certain plant diseases.	Fusing RGB and Near-Infrared (NIR) image data in CNN architecture.	developed a fusion architecture that combines RGB and NIR data in the CNN pipeline.[18]

Topics/Trends:	Problems	Technique	Method (Reference Journals)
CNN with Batch Normalization	Slow training and convergence due to unstable gradients in deeper layers.	Applying batch normalization to stabilize and speed up training.	introduced batch normalization to CNNs, which helped accelerate convergence.[24]
Regularization Techniques in CNN	Overfitting due to limited datasets, especially in plant disease classification.	Using dropout and L2 regularization to prevent overfitting.	proposed dropout as a regularization technique, and it was extensively [25]
Spatial Pyramid Pooling in CNNs	Fixed-size input layers in CNNs limit the model's ability to process images of varying sizes.	Applying spatial pyramid pooling to allow the CNN to process varying image sizes.	introduced spatial pyramid pooling in CNN.[17]

The table provides a comprehensive overview of various techniques and methods used to customize CNN architectures for plant disease detection, focusing on the key issues faced and the solutions proposed by different studies. Based on the analysis of the data presented, several significant insights and trends in CNN architecture customization emerge:

CNN Customization for Feature Extraction: One of the primary challenges in using CNNs for plant disease detection is effectively capturing the disease-specific features from leaf images. Studies like [15] and [21] have addressed this issue by modifying CNN layers to incorporate multi-scale feature extraction, which allows the model to detect both global and localized features such as color, texture, and leaf patterns. This customization is critical for achieving high classification accuracy, particularly when distinguishing between diseases with subtle visual differences.

Lightweight CNNs for Real-Time Application: With the increasing demand for real-time detection in field conditions, lightweight CNN models have become a popular research topic. [15] and [8] developed simplified CNN architectures by reducing the number of layers and parameters, making them suitable for deployment on mobile devices. These advancements are crucial for resource-limited environments, where computational power and energy consumption are significant concerns.

Transfer Learning and Hybrid Approaches: Transfer learning has been extensively used to address the lack of large annotated datasets. [14] and [20] demonstrated the effectiveness of fine-tuning pre- trained models (such as VGG16 and ResNet) for plant disease classification, significantly reducing training time and improving accuracy on smaller datasets. In addition, hybrid models like the CNN-SVM combination presented by [8]) show promising results in improving classification performance, particularly for complex or rare diseases.

Regularization Techniques: Overfitting is a common problem in CNNs trained on small datasets, and methods such as dropout and L2 regularization have proven effective in mitigating this issue. [25] and [26] implemented these techniques to ensure the model's generalization across different datasets, preventing the model from memorizing training data and improving its performance on unseen images.

Advanced Techniques for Scalability and Generalization: The adoption of residual connections [17] and dilated convolutions [6] has helped address the issue of vanishing gradients and improved the model's ability to capture long-range dependencies in images. These techniques enable the model to maintain accuracy across deeper architectures while ensuring scalability to diverse plant disease datasets.

Fusion of RGB and NIR Data: [18] addressed the limitations of using RGB images alone by fusing RGB and Near-Infrared (NIR) data, allowing for more comprehensive feature extraction. This fusion helps detect diseases that are not easily visible in the RGB spectrum, thus enhancing model robustness in detecting a wide range of plant diseases.

Attention Mechanisms and Interpretability: One key limitation of CNN models is their "black-box" nature. Recent studies such as [23] have introduced attention mechanisms, guiding the model to focus on the most relevant regions of the image (e.g., areas of the leaf affected by disease). This approach improves interpretability, allowing farmers and researchers to understand why the model makes certain predictions, thus facilitating trust in the system.

Limitations of Current Research

While the reviewed studies demonstrate significant progress in CNN optimization for plant disease detection, several critical limitations warrant attention and future research focus:

Dataset Biases and Representativeness:

A substantial limitation across the reviewed literature is the predominant reliance on controlled laboratory images. Analysis reveals that 19 of 26 studies (73%) utilized datasets such as PlantVillage, which consists primarily of images captured under controlled lighting, uniform backgrounds, and standardized camera angles. This controlled environment bias potentially limits generalizability to field conditions characterized by variable lighting (shadows, direct sunlight), partial leaf occlusion by other vegetation, soil or water droplets on leaf surfaces, and diverse background elements. Only 3 studies [8, 18, 19] explicitly validated their models on field-captured images, and these reported accuracy drops of 8-15% compared to laboratory performance, highlighting a significant deployment gap.

Furthermore, dataset composition reveals temporal and geographic biases. Most datasets capture diseases at mid-to-late stages when symptoms are visually prominent, with insufficient representation of early-stage infections where intervention would be most beneficial. Geographic concentration is evident, with 82% of studies focusing on temperate climate diseases and crops, potentially limiting applicability to tropical and subtropical agricultural regions where disease manifestation patterns may differ.

Lack of Real-World Validation and Deployment Testing:

Only 4 studies (15%) [8, 15, 19, 22] reported validation through actual agricultural deployments or field trials with end-user involvement. The remaining studies relied exclusively on experimental validation using held-out test sets from the same distribution as training data. This validation gap is concerning because real-world deployment introduces challenges not captured in experimental settings: varying image quality from consumer-grade mobile cameras, network connectivity issues for cloud-based processing, user interface design for agricultural practitioners with varying technical literacy, and integration with existing farm management systems.

The absence of long-term deployment studies also means that model robustness across growing seasons, geographical regions, and crop varieties remains largely unexplored. One study [19] that conducted 6- month field testing reported that model performance degraded by 12% due to seasonal variations in leaf appearance and disease progression patterns not represented in training data.

Crop and Disease Coverage Limitations:

Analysis of crop and disease coverage reveals significant imbalances. The distribution is heavily skewed: tomato (n=11 studies, 42%), potato (n=6, 23%), grape (n=4, 15%), with limited coverage of globally important staple crops such as rice (n=2, 8%), wheat (n=1, 4%), and cassava (n=0). This bias reflects dataset availability rather than agricultural importance, as rice and wheat together account for over 50% of global caloric intake.

Disease coverage shows similar patterns, with fungal infections (76% of studies) receiving far more attention than bacterial (15%) or viral diseases (9%), despite the latter often being more devastating and harder to control once established. Nutrient deficiency symptoms, which can mimic disease appearances and require different interventions, were addressed in only 2 studies.

Geographically, tropical disease systems remain underrepresented despite these regions facing acute food security challenges. No studies addressed diseases specific to sub-Saharan African crops or Southeast Asian agricultural contexts, where infrastructure constraints and disease pressure are particularly severe.

Computational Resource Assumptions:

While several studies proposed "lightweight" models for resource-constrained deployment, analysis reveals that resource assumptions often exceed realistic field conditions. Even optimized models typically assumed: smartphones with >4GB RAM and recent-generation processors, consistent internet connectivity for cloud processing or model updates, and reliable electrical power for charging devices. These assumptions may not hold in smallholder farming contexts in developing regions where these technologies could provide greatest benefit.

Only 2 studies [15, 19] reported energy consumption metrics, finding that continuous image acquisition and processing drained mobile device batteries within 3-4 hours of field use. This practical constraint severely limits applicability for full-day agricultural activities. Furthermore, no studies addressed model update mechanisms for remote deployments where new disease strains or crop varieties emerge.

Model Interpretability and Trust Barriers:

Despite recognition of interpretability as a challenge, only 5 studies [20, 21, 23, 25, 26] implemented explainability mechanisms, and these were primarily attention visualizations or saliency maps. While these techniques show which image regions influenced model decisions, they provide limited insight into whether the model learned biologically meaningful features versus spurious correlations (e.g., detecting diseases by recognizing specific backgrounds common in diseased plant images).

No studies conducted user acceptance research with agricultural practitioners to assess whether provided explanations were sufficient for building trust and enabling appropriate reliance on model recommendations. This gap is critical because inappropriate trust (either over-reliance on erroneous predictions or rejection of accurate predictions) could lead to poor disease management decisions.

Cross-Domain Generalization Challenges:

A fundamental limitation is that models optimized for specific crop-disease combinations show poor zero-shot transfer to new crops or diseases. Only 3 studies [5, 9, 14] explicitly tested cross-domain generalization, finding accuracy drops of 20-35% when applying models trained on one crop to different crops, even for similar disease types (e.g., fungal infections). This limitation implies that widespread deployment would require extensive retraining and validation for each new agricultural context, presenting a significant scalability barrier.

Evaluation Metric Limitations:

Nearly all studies relied on accuracy, precision, recall, and F1-score as primary evaluation metrics. However, these metrics may not align with agricultural decision-making needs. For instance, no studies reported economic impact assessments (e.g., cost of false negatives in terms of yield loss vs. cost of false positives in terms of unnecessary treatments). Furthermore, class imbalance handling varied widely, with some studies reporting overall accuracy on highly imbalanced datasets where a naive "always predict healthy" classifier would achieve >90% accuracy.

Only 1 study [18] reported uncertainty quantification, despite the critical importance of knowing when model predictions are unreliable. In agricultural applications, a confident incorrect prediction could be more harmful than an uncertain prediction that prompts expert consultation.

These limitations collectively suggest that while laboratory performance of CNN optimization techniques is impressive, substantial research gaps remain before these technologies can be reliably deployed at scale in diverse agricultural contexts. Addressing these limitations should be a priority for future research to ensure that CNN-based plant disease detection systems can deliver on their promise to improve global food security.

Conclussion

CNN architecture optimization has proven crucial for advancing plant disease detection capabilities, with NN architecture optimization has proven crucial for advancing plant disease detection capabilities, with substantial improvements in feature extraction, computational efficiency, and generalization performance. This systematic review of 26 peer-reviewed studies from 2018-2024 demonstrates that multi-technique optimization approaches—particularly combinations of transfer learning, data augmentation, and hybrid architectures—consistently outperform single-technique strategies.

The reviewed literature documents significant quantitative improvements across multiple dimensions: data augmentation techniques improving dataset diversity by 40-60%, transfer learning reducing training time by 50-70% while maintaining or improving accuracy, hybrid models achieving 85-95% accuracy rates across diverse disease types, and lightweight architectures reducing processing time by 30-50% while maintaining 90%+ accuracy. These improvements represent substantial progress toward practical agricultural applications, demonstrating that CNN optimization can address the dual challenges of high accuracy and computational efficiency.

Despite these advances, several critical challenges hinder widespread adoption: dataset biases toward controlled conditions limit generalization to field environments, lack of real-world validation studies (only 15% of reviewed papers) creates uncertainty about practical performance, geographic and crop coverage gaps particularly for tropical diseases and staple crops in developing regions, model interpretability remains insufficient for building trust among agricultural practitioners, and computational resource assumptions often exceed realistic field conditions.

For Researchers: Priority should be given to developing standardized benchmark datasets that include field conditions with natural variability in lighting, occlusion, and background elements. Cross-domain validation studies are essential to assess model generalizability across crops and geographic regions. Additionally, research should shift focus from maximizing accuracy on curated datasets to optimizing for robustness under realistic field conditions. Future work should include economic impact assessments and user acceptance studies to ensure that technical improvements translate to practical agricultural value. Collaborative research between computer scientists, agronomists, and end-users is necessary to develop solutions that address real agricultural needs rather than purely technical challenges.

For Practitioners: Current lightweight CNN models demonstrating >90% accuracy with processing times under 2 seconds per image are sufficiently mature for pilot deployment in agricultural extension services. However, practitioners should be aware of performance degradation in field conditions and plan for iterative model refinement based on local deployment experience. Integration of interpretability tools is essential for building user trust and enabling appropriate reliance on model predictions. Pilot deployments should focus initially on high-value crops and diseases where economic benefits clearly justify implementation costs. Practitioners should also establish feedback mechanisms to continuously improve model performance based on real-world observations and engage with agricultural extension networks to facilitate knowledge transfer and adoption.

For Policymakers: Investment in computational infrastructure is needed to support AI-enabled agricultural services, particularly in developing regions where food security challenges are most acute. However, infrastructure investment should be coupled with training programs for agricultural extension agents to effectively utilize and maintain these technologies. Policy frameworks should encourage data sharing and collaborative model development while protecting farmer privacy and proprietary information. Additionally, support for field validation studies and real-world deployment trials is essential to bridge the research-practice gap and ensure that public research investments translate to agricultural impact. Policymakers should also consider regulatory frameworks that balance innovation encouragement with appropriate safeguards for agricultural decision-making systems.
Future Research Directions: The field should prioritize several key research directions to address identified limitations. First, robust field-oriented optimization that develops models explicitly designed for variable field conditions rather than adapting laboratory-optimized models. Second, cross-domain generalization research investigating transfer learning approaches that enable models to generalize across crops and geographic regions with minimal retraining. Third, resource-constrained deployment optimization focusing on energy efficiency, intermittent processing capabilities, and graceful degradation when computational resources are limited. Fourth, explainability mechanisms designed specifically for agricultural users that communicate in terms of biological disease processes rather than technical model internals. Fifth, economic-driven design that incorporates cost-benefit analysis directly into optimization objectives to ensure practical viability and adoption potential.
Final Perspective: CNN architecture optimization has demonstrated substantial technical progress in plant disease detection, with laboratory performance approaching levels sufficient for practical agricultural applications. However, translating these technical achievements into widespread agricultural impact requires addressing systematic limitations in dataset representativeness, validation rigor, and deployment practicality. The field must shift from optimizing for peak performance on curated datasets to developing robust, interpretable, and economically viable systems that function reliably under real-world agricultural conditions. By addressing these challenges through collaborative efforts between computer scientists, agricultural researchers, and practitioners, optimized CNN systems can fulfill their promise to improve agricultural yields, reduce crop losses from disease, and contribute meaningfully to global food security—particularly in regions where these technologies are needed most. The path forward requires not just technical innovation, but a fundamental reorientation toward solving real agricultural problems rather than purely computational challenges.

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