

Systematic Review of a Convolutional Neural Network for Detecting Tomato Leaf Disease

Amina Abdulmumin Umar

umaraminaa133@gmail.com

Federal University

Taiwo Kolajo

Federal University

Joshua Babatunde Agbogun

Federal University

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Abstract

The agricultural sector is facing an increasing number of diseases of plants, particularly factors that have a significant impact on tomato plants, which can have a major effect on their quality and productivity. Timely management and action depend on accurate disease detection. Image classification tasks have made extensive use of Convolutional Neural Networks (CNNs). However, they face limitations in capturing global contextual information, which can lead to potential inaccuracies. This study reviews existing literature on the use of CNNs and hybrid models for tomato leaf disease detection, covering literature published between 2014 to 2024. A structured database search initially identified 2,591 records, of which 29 peer-reviewed studies met the inclusion criteria for detailed analysis. The study also examines the role of the nutrients present in tomato leaves, symptoms of disease, and their impact on productivity. The review evaluates CNN architectures, transfer learning models, lightweight networks, and hybrid approaches, focusing on datasets, preprocessing methods, and performance outcomes. Reported accuracies often exceed 95% on benchmark datasets, but performance declines sharply in field conditions due to variable environments, class imbalance, and limited dataset diversity. Three major challenges emerged: weak generalization beyond controlled data, high computational costs for deployment, and the absence of robust, field-oriented datasets. Recent advances, including transformer-enhanced CNNs, attention mechanisms, lightweight architectures, and pruning techniques, show promise in addressing these gaps. This review consolidates evidence, identifies limitations, and outlines future directions for plant disease detection that are resource-efficient, explainable, and real-time systems for sustainable agriculture.

1 Introduction

Tomato (*Solanum lycopersicum*) is a staple crop worldwide, valued for its nutritional content and economic significance. It belongs to the Solanaceae family and is renowned for its diverse fruit colors and shapes. Tomatoes are a significant vegetable crop worldwide, native to South and Central America, and are particularly vital in African home gardens. They offer nutritional benefits, serving as a cash crop for farmers and a culinary staple for their flavor-enhancing properties. Determinate and indeterminate types are the two varieties of tomatoes, which influence growth habits and fruit production timelines [1]. In addition to being a basic food, tomatoes are an excellent source of potassium, vitamins A and C, and antioxidants. Because of their high nutritional content and many culinary uses, tomatoes are an essential crop in both industrialized and developing nations [2].

CNNs have been suitable for identifying plant diseases because of their excellent performance in imagery categorization tasks. CNNs, however, struggle with the identification of contextual linkages and lengthy interdependence within images [3]. Transformer-based models have recently drawn interest in computer vision because of their capacity to use attention mechanisms to interpret global features [4]. Enhancing feature extraction by integrating transformer attention approaches with CNNs can improve disease detection and classification efficiency [5].

This work provides a systematic review of a CNN-based tomato leaf disease detection model, providing an overview of research, findings, and implications for practice. It examines different CNN architectures, data augmentation techniques, datasets, benchmark results, performance metrics, challenges, and provides recommendations and prospects for further study.

This review's succeeding sections are structured as follows: Section 2 discusses the background, including tomato leaf nutrients, diseases, and prior work; Section 3 details the methodology, research questions, and selection process; Section 4 and 5 presents the discussion of findings; Section 6 highlights the limitations of the review; Section 7 outlines subsequent directions; and Section 8 contains significant conclusions and suggestions for improving tomato leaf disease detection with CNN-based algorithms.

2 Background and Related Research

2.1 Nutrients in Tomato Leaf

Tomato leaves are vital to fruit production due to their role in photosynthesis, nutrient uptake, water regulation, disease resistance, and hormone production. These processes are essential for the growth and development of tomato fruits. Healthy leaves ensure efficient energy conversion from sunlight, which drives fruit formation and ripening. Additionally, they regulate water and nutrient flow within the plant, directly impacting fruit quality and yield. Maintaining healthy foliage is critical for maximizing tomato production and ensuring high-quality fruits [6]. Table 1 shows the roles in tomato leaves and their functions.

Table 1: Role of Nutrients in Tomato Leaves and Their Functions [7]

Nutrient	Function
Nitrogen (N)	Protein and amino acid constituents
Phosphorus (P)	component of nucleic acids.
Potassium (K)	Activates the pyruvate kinase and other enzymes that control the tomato fruit's pH level.
Magnesium (Mg)	A component of chlorophyll
Calcium (Ca)	Part of the cell wall of plants. It has an impact on cell membrane permeability.
Sulfur (S)	A component of amino acids and proteins, such as methionine
Boron (B)	Controls the amount of growth chemicals
Iron (Fe)	Enzyme components, such as catalase and peroxidase
Manganese (Mn)	renders enzymes (like malic) active.
Copper (Cu)	An active component in oxidizing enzymes, such as phenolase
Zinc (Zn)	The carbonic anhydrase enzyme's component
Molybdenum (Mo)	Engages in the use of nitrate reductase, or NO ₃ -N

2.2 Tomato Leaf Diseases

Plant diseases can generally affect different plant parts, such as roots, leaves, and flowers. One of the most noticeable and prominent features of a plant is its leaves. Because photosynthesis in leaves produces chlorophyll from sunlight, leaves can contribute to the provision of nutrients the plant needs to flourish [8]. The productivity and even survival of the plant may be directly impacted by diseases that cause leaves to drop or wither. It will also have negative impacts, leading decrease in yields and an increase in the cost of production [9]. Table 2 presents the list of typical tomato leaf diseases along with their symptoms.

Table 2: Symptoms of Tomato Leaf Diseases [10]

S/N	Disease Name	Causes/Pathogen	Symptoms	Comments
1	Early Blight	A fungus called Alternaria solani . Thrive in warm humid conditions, it spreads through wind, contaminated tools, and water splash	Small, dark brown spots on lower leaves, often concentric rings. Spot enlarged and may merge.	Severe infections cause defoliation. This fungus can live in the soil over the winter
2	Bacteria Spot (Xanthomonas vesicatoria)	Bacteria	Small, water-soaked spots on leaves that become brown or black with a halo. Spots may be raised and have a greasy appearance.	It affects the fruit when not detected early
3	Late Blight (Phytophthora infestans)	Oomycete: a fungus-like organism	Water-soaked spots on leaves often start at the edges. This spot can quickly enlarge to black or brown. White cottony growth can emerge on the underside of leaves in humid conditions	This can kill the entire plant rapidly
4	Leaf Mold (cladosporium fulvum)	Fungus, favored by high humidity and poor air circulation	Yellow spots on the upper leaf surface with brownish or grayish mold on the underside.	It affects older leaves primarily
5	Mosaic Virus	Virus. It spreads by contaminated tools, plant contact, and sometimes seeds	Mottling, the light and dark green areas on leaves.	Foliage can become distorted or curled, and stunted growth may occur
6	Septoria Leaf Spot	A fungus called Septoria lycopersici that infects foliage. It spreads by splashing water or through the wind	Small circular spots with grayish-white centers and dark borders. Numerous spots can appear on a single leaf	Lower leaves are usually affected first
7	Target Spot (Alternaria alternata)	Fungus. Usually a secondary infection after other stresses.	The symptoms are similar to early blight but spots may be more irregular and less likely to have concentric rings	It is often confused with early blight
8	The Yellow Leaf Curl Virus	Virus. Spread by whiteflies	Yellowing and curling of young leaves, especially at the top of the plant	Lead to severe stunted growth
9	Spider Mites (two-spotted mites)	Tiny mites. Thrive in dry, hot conditions	Yellowing, or fine stippling on leaves. They may be evident threads, especially on the undersides of the leaves	Severe infection can cause leaf drop

Healthy Tomato Foliage is a vibrant, fully functional organ that contributes significantly to the plant's overall well-being and productivity. It is a key indicator of plant health and reflects the complex interplay of physiological processes and interactions with the environment. Figure 1 below shows the pictorial view of unhealthy and healthy leaves

2.3 Related Research

The earlier research on a review of CNN-based models for tomato leaves is presented in this section, with Table 3 providing a summary of what the previous papers have achieved compared with what the present paper has done

[11] reviews CNNs in the context of disease detection on plant leaves, analyzing 100 articles published over the past five years. The review identifies that Deep Convolutional Neural Networks (DCNNs) are the best techniques for early disease detection and discusses popular CNN frameworks, including Keras, Caffe, Torch, and TensorFlow. The paper compares various CNN models, including already trained networks like ResNet50 and AlexNet, as well as models trained from scratch. However, it highlights limitations and challenges in using CNNs for plant leaf disease detection, including the scarcity of large datasets, the impact of

image background, and the variability of plant disease symptoms. The paper also emphasizes the need for new requirements, larger datasets, and novel architectures to advance the field. Similarly to this, [12] reviews 38 studies on deep learning (DL) methods used in image processing tasks for tomato plants, with the range of 2016-2020. They examined areas of application, data preprocessing methods, transfer learning, and data augmentation techniques to assist future researchers in developing more precise systems and addressing research gaps in the field of agriculture. DL techniques generally outperform other image processing methods, but their performance is heavily dependent on the dataset used. Direct comparison between individual papers proved challenging due to variations in samples, train-to-test ratios, performance metrics, preprocessing techniques, architectures, parameters, and hyperparameters. The paper also highlights the effectiveness of DL but notes that it still faces diverse challenges and obstacles, suggesting further research for its broader adoption in sustainable agriculture.

[13] In their study examined the application of deep learning and computer vision in leaf disease classification, focusing on the significance of deep learning in plant disease detection. They reviewed various deep learning architectures (like TensorFlow, Keras, Caffe, and PyTorch) and their contributions. The study also discusses the use of public databases like PlantVillage and Kaggle, as well as custom datasets. The research reveals that machine learning and computer vision are adaptable and significant in plant disease detection, with researchers continuously enhancing existing architectures and introducing new ones. The efficiency of TensorFlow, Keras, Caffe, and PyTorch makes them preferred, while public datasets like PlantVillage, Kaggle, and ImageNet are commonly used due to their abundant labeled data. The study also highlights the need for larger datasets, greater model robustness, and scalability with current technology. This adaptability of deep learning with computer vision reveals the continuous nature of this research area. In another study, [14] a thorough review of deep learning methods for the detection of tomato leaf diseases, highlighting the crucial role of agriculture in India's economy and the vulnerability of tomato plants to various diseases. The review focuses on deep learning-based Convolutional Neural Networks (CNNs) architectures, such as DenseNet, ResNet, VGG Net, Google Net, Alex Net, and LeNet, applied to identify 10 classes of diseases affecting tomato plant leaves. It addresses current research gaps by guiding the continued development and deployment of tools for tomato leaf noting that the DenseNet model had the highest average validation accuracy for detecting tomato leaf diseases. disease diagnosis and management. The report also addresses the classification of tomato leaf diseases into fungal, bacterial, and viral groups, including specific illnesses like Bacterial Spot, Early Blight, Late Blight, and Yellow Leaf Curl Virus. Furthermore, the study assesses the effectiveness of various CNN models, including DenseNet, VGG-19, and ResNet, for disease identification in tomato plants.

Table 3: Summary of Related Review and Justification of the Review

Author/Year	What Existing Review Has Achieved	What the Current Study has Done Differently
[11]	These authors conducted a broad review of CNN applications for various plant leaf diseases across crops. They reported that VGG, ResNet, and MobileNet achieved approximately 99% accuracy on PlantVillage. Highlighting preprocessing importance but noted poor generalization in field conditions. Suggesting the need for larger datasets and stronger architectures	The current paper conducted a Tomato-specific, systematic review of 2,691 which were narrowed down to 29 papers after applying the inclusion and exclusion criteria. Emphasizing the lab-to-field performance gap, the authors review lightweight CNNs, transfer learning, transformer-enhanced models, and deployment strategies (TensorFlow Lite, pruning, quantization, IoT). It also includes agronomic context (nutrients, symptoms).
[12]	Reviewed 38 papers (2016–2020) applying deep learning to tomato plants, covering disease and pest detection, fruit classification, macronutrient deficiency, and weed detection. Summarized datasets, preprocessing, augmentation, transfer learning, and CNN/advanced architectures such as YOLO, SSD, Mask R-CNN. Found that Deep Learning performed better than the traditional methods, but results depended heavily on dataset quality. The paper suggested further work on nutrient deficiency and weed detection	This paper adopts More recent and methodologically systematic considering papers within the range of 10 years (2014 - 2024), with PRISMA-style filtering of 2,691 to 29 papers. Focusing on tomato leaf disease for deeper analysis. It also Highlights real field performance gaps, covers transformer enhanced CNNs, and proposes deployment-ready solutions (Lite, pruning, IoT, explainable AI, multimodal data).
[13]	Conducted a systematic literature review (SLR) of 101 studies from 2015 to 2024 using PRISMA style. They covered multiple crops (tomato, rice, apple, potato, maize, grape, citrus, soybean, etc.) and tasks such as disease detection, classification, severity estimation, and early prediction. The paper highlighted the role of transfer learning, hybrid CNN-transformer models, segmentation, and ensembles. Reported that no single model is best but noted growing use of transfer learning and CNN-transformer hybrids. Discussed popular tools (TensorFlow, Keras, PyTorch, MATLAB, OpenCV) and reliance on datasets like PlantVillage, Kaggle, and ImageNet.	Although the present study is narrower but deeper, focusing exclusively on tomato leaf disease (2014–2024). It screened from 2,691 to 29 papers with PRISMA-style inclusion, exclusion and explicit research questions (RQ1–RQ5). Unlike Yani et al., it provides concrete evidence of the lab-to-field performance gap, reviews lightweight CNNs, pruning, quantization, TensorFlow Lite, IoT integration, and explainable AI, and offers an agronomic perspective (nutrients, symptoms). This makes the review more application-driven and field-ready compared to Yani et al. broader survey.
[14]	Reviewed various CNN architectures (AlexNet, VGGNet, GoogLeNet, ResNet, Inception, DenseNet, MobileNet) used in plant disease detection. Surveyed datasets (PlantVillage, ImageNet, self-collected), preprocessing (augmentation, normalization), and training strategies. Concluded CNNs achieve high accuracy but face challenges in real-time detection, computational cost, and dataset dependency. Suggested future research on hybrid CNN models, lightweight architectures, and transfer learning.	While Vengaiah & Konda, (2023) broadly reviewed CNNs for all plant diseases, this study narrows down to tomato leaf disease only, but introduces explicit research questions (RQ1 - RQ5), and it goes further by stressing the field deployment challenges (real-time IoT integration, pruning, quantization, TensorFlow Lite). It also discusses transformer-enhanced CNNs and explainable AI, which were not addressed in their review.

3 Methodology

The basis of this research was a thorough review of studies on a CNN-based model for the detection of tomato leaf disease. This study adopts a systematic review structure from [15], where several literatures were reviewed using the search strategy, including inclusion and exclusion criteria.

3.1 Research Question (RQ)

This research addresses the following research questions:

RQ1: In the literature, which CNN-based architecture types were previously utilized to detect tomato leaf disease?

RQ2: What datasets and data preprocessing/augmentation strategies have been used in CNN-based Tomato leaf disease detection?

RQ3: What is the reported performance (accuracy, F1-score, precision, recall) of CNN-based models for detecting tomato leaf disease?

RQ4: What are the primary challenges and limitations identified in applying CNN models for the detection of tomato leaf disease?

QR5: How can CNN-based models be made more accurate, robust, and deployment-ready?

3.1 Search Strategy

We explore several literatures from different sources, such as Semantic Scholar, IEEE Xplore, Research Gate, ScienceDirect, using the following strings

- i. "Tomato leaf disease detection" AND ("CNN" OR "Convolutional Neural Network" OR "deep learning")
- ii. "CNN-based model for tomato leaf disease detection".

3.2 Selection Process

The search was conducted with the 4 strings using the BOOLEAN operators “OR” and “AND”, which returned a total of 2691 records as shown in Table 4 from the strings in section 3.1 above.

Table 4: First Search String Result

Publishers	IEEE Xplore	MDPI	ScienceDirect	Schematic Scholar	Springer	ResearchGate	Total
No. of Papers	293	15	85	911	1580	100	2591

Further refinement was carried out based on the publication year, ranging from 2014 to 2024. This resulted in the exclusion of 406 papers, leaving a total of 2185 papers, as shown in Table 5. In the third search, the scope was limited to the field of computer science, specifically selecting only conference papers and journal articles on machine learning, while excluding review papers, blogs, and books. The results of this search are presented in Table 6. We further narrowed the selection by carefully reviewing the paper titles, abstracts, and introductions to identify relevant research articles and journals that include complete implementations of deep learning and machine learning applications, excluding duplicates. Table 7 presents the details of the papers that were manually reviewed in relation to the research questions.

3.3 Inclusion Criteria

From the search results, we only considered journals that focus on deep learning models, specifically CNN-based models for tomato leaf disease detection using image datasets and hybrid architectures. We included journals written in English from 2014 to 2024, which clearly state their methodology and evaluate performance using at least one metric (F1 Score, Accuracy, Precision, or Recall).

Table 5: Second Search Filtered Based on Year of Publication

Publishers	IEEE Xplore	MDPI	ScienceDirect	Sematic Scholar	Springer	ResearchGate	Total
No. of Papers	255	12	49	687	1182	76	2185

Table 6: Third Search

Publishers	IEEE Xplore	MDPI	ScienceDirect	Semantic Scholar	Springer Link	ResearchGate	Total
No. of Papers	255	11	40	22	580	75	910

Table 7: Fourth Search

Publishers	IEEE Xplore	MDPI	ScienceDirect	Schematic Scholar	Springer	ResearchGate	Total
No. of Papers	7	8	9	2	3	29	29

3.4 Exclusion Criteria

Exclusion criteria also included not considering other plant diseases, journals without image datasets, journals published before 2014, non-English journals, journals without deep learning implementation, conference abstracts only, and blogs were not included

4 Results/Findings

In this section, a comprehensive literature review CNN models used in plant disease detection and classification tasks was conducted to identify the most effective architectural components for enhancing CNN feature extraction based on the research questions that guide the search

RQ1: In the literature, which CNN-based architecture types were previously utilized to detect tomato leaf disease?

The reviewed studies employed a wide range of CNN architectures for detecting tomato leaf disease, reflecting both advances in deep learning and adaptations for agricultural constraints. Early works designed custom CNNs of varying depths, typically consisting of convolutional layers, pooling, and fully connected layers to classify tomato leaf images [16, 17,18]. More recent studies emphasized lightweight CNN architectures optimized for edge deployment, such as MobileNetV2/V3, GoogleNet, EfficientNet, SqueezeNet, NasNetMobile, and LightMixer CNN, which combine high accuracy with reduced computational overhead [19, 20,21]. In parallel, classical deep CNNs such as VGG16, VGG19, ResNet-34/50, Inception V3/ResNet V2, and DenseNet-201 were widely applied through transfer learning, achieving state-of-the-art accuracy on benchmark datasets [22, 23, 24, 25]. Beyond these, several works explored hybrid and fusion models, which combined CNNs with attention mechanisms, handcrafted features, or traditional classifiers such as SVMs to enhance feature extraction and interpretability [26, 27,28]. Other researchers extended CNNs into object detection frameworks, employing Faster R-CNN, YOLOX-S, YOLOv7, and PLPNet to perform simultaneous disease localization and classification (29, 30, 28, 31)). A few studies advanced further by experimenting with Capsule Networks (CapsNet) to capture spatial hierarchies [32], GAN-augmented CNNs to generate synthetic training data [33, 34], and even multimodal vision transformer frameworks with CNN backbones for open-vocabulary detection [35]. Additional enhancements included tensor subspace learning (HOWSVD–TEDA) fused with CNN features [36] and ensemble learning strategies [37]. Collectively, these architectural variations highlight an evolution from traditional CNN classifiers toward lightweight, hybrid, and transformer-enhanced designs that prioritize both performance and deployment readiness.

RQ2: What datasets and data preprocessing/augmentation strategies have been used in CNN-based Tomato leaf disease detection?

A consistent pattern across the literature is the heavy reliance on the PlantVillage dataset, or its Kaggle derivatives, which provided standardized tomato leaf images under controlled laboratory conditions (16, 22, 24, 21). While PlantVillage was the most widely adopted, a growing number of studies supplemented it with field datasets to address real-world variability. For example, [34] collected images from Mexican farms, [25] added field images from Egypt, [38] used Malawian farms, [19] worked with Ghanaian farms, and [28] curated greenhouse datasets in China. Specialized datasets were also used, including the Taiwan dataset [36] and the AI Challenger dataset [31]

Preprocessing strategies varied but included resizing, normalization, and standard augmentations such as rotation, flipping, scaling, and zooming to expand training data artificially [38]. Color-space transformations were especially effective, with RGB-to-HSV and RGB-to-CMYK conversions enhancing feature visibility and improving model accuracy [22, 24]. To reduce background interference, Classification approaches, including HSV thresholding, black background masking, and SIFT-based region extraction, were utilized [24, 28]. Synthetic enhancement furthermore proved as a promising strategy, with GANs generating realistic artificial images [33, 34]. Additionally, SMOTE was used to address class imbalance [41]. These preprocessing and augmentation methods highlight the importance of dataset diversity and realism for developing generalizable CNN models.

RQ3: What is the reported performance (accuracy, F1-score, precision, recall) of CNN-based models for detecting tomato leaf disease?

Performance outcomes across the reviewed studies consistently show high results when models are evaluated on controlled datasets, such as PlantVillage. Many studies reported near-perfect classification accuracies, including DenseNet-201 (99.4%) [23], ResNet-50 with Gaussian preprocessing (99.53%) [22], Inception V3 with dropout (99.22%) (Saeed et al., 2023), LightMixer CNN (99.3%) [21], and DTomatoDNet (99.34%) [40]. Alternative approaches, including GoogleNet, MobileNetV2, EfficientNet, as well as the VGG, attained high ratings of performance between 95% and 98% on the identical datasets [27, 20, 24]. Hybrid and lightweight CNNs tended to produce slightly lower performance, generally between 87% and 92%, especially when using SMOTE balancing or GAN-generated synthetic data [16, 41, 33].

By contrast, when tested in field conditions, accuracies dropped sharply. [42] achieved 95% validation accuracy but only 64% to 70% when tested in the field, while [38] reported less than 10% field accuracy despite achieving over 90% on PlantVillage. Similarly, [19] observed overfitting, with training accuracy near 97% but validation accuracy dropping to approximately 68%. For detection/localization models, performance was typically expressed as mAP (mean average precision): Faster R-CNN with attention achieved 0.981 mAP [29], PLPNet achieved 94.5% mAP50 [30], and an improved Faster R-CNN reached 96.4% classification accuracy and 89.5% mAP [43]. Collectively, these results highlight the disparity between lab-based success and field generalization, raising concerns about real-world reliability.

RQ4: What are the primary challenges and limitations identified in applying CNN models for the detection of tomato leaf disease?

The most fundamental constraint highlighted across studies is the generalization difference between laboratory datasets and real-world field conditions. Models trained on PlantVillage often achieve near-perfect performance but fail dramatically when tested on field images, as demonstrated by [38] and [42]. This gap arises primarily from the uniform background and controlled lighting of PlantVillage, which does not reflect the variability of farm conditions [23, 44]. Another key issue is dataset imbalance, where some diseases are underrepresented, leading to poor sensitivity for rare classes [24]. Moreover, most datasets assume single-label classification, while in practice, leaves may suffer from multiple diseases simultaneously, a limitation noted by [40].

From a technical perspective, challenges include computational constraints, especially for transformer-enhanced, attention-heavy, or tensor-based CNN models, which require substantial resources and thus hinder deployment on mobile or IoT devices [35, 36]. Even lightweight CNNs face latency and power issues when deployed in real-time environments [20, 37]. Models that employ GANs or synthetic augmentation also face risks of false positives and false negatives, reflecting the limitations of artificially generated data [33]. Finally, real-world conditions such as lighting variation, occlusion, overlapping leaves, and background complexity remain significant barriers to consistent performance [34]. These limitations suggest that despite strong progress, CNN-based methods require significant adaptation before they can be considered reliable in real farming scenarios.

QR5: How can CNN-based models be made more accurate, robust, and deployment-ready?

To address these challenges, various strategies have been proposed. Data-focused solutions include expanding datasets with field and multi-regional images [38, 25], generating synthetic images using GANs [34], and applying SMOTE to rebalance classes [41]. Model-focused strategies involve incorporating attention mechanisms and transformer modules to enhance feature learning ([26, 28, 35], designing lightweight CNNs through pruning and parameter reduction [17, 37, 21], and leveraging ensemble or fusion techniques to combine handcrafted and deep features [27, 36]. Deployment-oriented strategies emphasize pruning, quantization, and conversion to lightweight formats such as TensorFlow Lite for mobile and embedded devices [19, 20]. Additionally, IoT

integration is proposed to enable real-time monitoring in agricultural environments [30, 44]. Finally, several studies suggest continuous or online learning approaches, where models are updated dynamically as new field data become available [28]. Collectively, these strategies illustrate a shift from focusing exclusively on maximizing accuracy to building robust, resource-efficient, and field-deployable solutions for detecting tomato leaf disease.

4.1 Summary of Findings

This systematic review shows that CNNs, as well as their variants, have demonstrated strong performance on the detection of tomato leaf diseases. Combining custom CNN architectures and transfer learning models like DenseNet, ResNet, VGG, and EfficientNet frequently achieved accuracies above 95%, with some exceeding 99%. Lightweight models, including MobileNet and compact CNNs, further highlight opportunities for deployment in resource-constrained environments. Preprocessing methods, notably color-space transformation, segmentation, and data augmentation, consistently enhanced feature extraction and model robustness.

However, the findings also reveal a persistent performance gap between controlled and real-world environments. While benchmark datasets such as PlantVillage supported near-perfect results, field conditions with variable lighting, occlusion, and background complexity reduced accuracy significantly. Hybrid models, transformer-enhanced CNNs, GAN-based augmentation, and ensemble strategies were identified as promising solutions for improving generalization and robustness.

5 Discussion

From the findings, it is obvious that CNN-based techniques remain one of the leading approaches in the detection of tomato diseases detection research. Their high classification accuracy, together with flexibility in architecture design, has made them the ideal choice for plant pathology applications. Transfer learning from pre-trained models has allowed researchers to leverage existing deep architectures, achieving state-of-the-art outcomes on benchmark datasets. Meanwhile, lightweight CNNs demonstrate the potential for deployment on mobile and IoT platforms.

However, the consistent generalization gap highlights a central challenge: performance achieved under controlled laboratory conditions does not translate reliably to farm-level applications. Models trained primarily on datasets such as PlantVillage struggle with environmental variability, making them less effective in real-world scenarios. Additionally, while complex models incorporating transformers or ensemble techniques improve feature learning, they often impose high computational costs, limiting their feasibility for low-resource deployments.

Real-time detection frameworks like Faster R-CNN and the YOLO algorithm represent a step forward by enabling both localization and classification. Yet, their technical complexity may restrict adoption by smallholder farmers. Similarly, augmentation methods such as GAN-generated datasets or SMOTE balancing improve dataset diversity but may introduce artificial biases, raising questions about reliability under field conditions. Thus, while CNN-based solutions have advanced significantly, their field readiness remains limited.

6 Limitations of the Review

Several methodological constraints must be acknowledged. The literature search was restricted to specific databases (IEEE Xplore, MDPI, ScienceDirect, Semantic Scholar, and Springer), which may have excluded relevant studies indexed in other databases. Only English-language publications from 2014 to 2024 were considered, possibly omitting valuable contributions in other languages or outside this timeframe. The inclusion criteria focused exclusively on CNN-based methods for the detection of tomato leaf disease, excluding non-CNN approaches and non-image modalities such as hyperspectral or thermal sensing, which may have provided additional insights.

Additionally, non-peer-reviewed content, including conference abstracts, blogs, and preprints, was excluded. While this ensured quality, it may also have overlooked emerging research that had not yet been formally published. Finally, this review synthesized findings qualitatively rather than through a quantitative meta-analysis, which limits the comparability of reported performance metrics across studies.

7 Future Directions

Further studies should emphasize the acquisition of large, diversified, and field-oriented datasets that reflect real agricultural environments. Such datasets should incorporate variability in geography, climate, cultivation practices, and disease co-occurrence to improve generalization. Expanding beyond single-label classification to models capable of detecting multiple simultaneous infections is also essential for practical use.

Hybrid architectures that combine CNN with transformers, attention mechanisms, and pruning strategies should be further explored to balance contextual feature learning with computational efficiency. The incorporation of multimodal data, such as soil conditions, climate data, and multispectral imagery, may enhance diagnostic accuracy and resilience.

Deployment optimization remains critical. Lightweight architectures, quantization, pruning, and conversion into mobile-ready formats (e.g., TensorFlow Lite) are necessary for real-time use in resource-limited settings. Continuous and adaptive learning frameworks could allow models to update dynamically with new field data, enhancing long-term robustness. Finally, explainable AI methods must be incorporated to improve interpretability, build trust, and encourage adoption among farmers, agricultural advisors, and policymakers

8 Conclusions

This systematic review set out to evaluate the effectiveness of CNN models for the detection of tomato leaf disease, motivated by the urgent need to reduce yield losses from fungal, bacterial, and viral infections. A structured search across multiple databases initially identified 2,691 records. Through successive filtering by year, language, subject area, and methodological rigor, a focused set of peer-reviewed studies published between 2014 and 2024 was selected. Inclusion criteria emphasized CNN-based models employing image datasets with clear methodological descriptions and performance evaluations, while exclusion criteria eliminated non-English works, non-image approaches, non-peer-reviewed content, and incomplete studies.

The findings confirm that CNN-based models ranging from lightweight custom designs to advanced transfer learning architectures achieve consistently high accuracy on benchmark datasets, particularly PlantVillage. Preprocessing and augmentation techniques further enhanced robustness, while hybrid and transformer-enhanced CNNs offered improved feature learning capabilities. However, the review also identified a critical limitation: the generalization gap between controlled environments and real-world farming conditions. Field trials consistently revealed reduced accuracy due to environmental variability, underscoring the need for more diverse and realistic datasets.

By consolidating evidence from a decade of research, this review contributes both a synthesis of CNN effectiveness and an analysis of the gaps that continue to hinder real-world adoption. It underscores that progress must extend beyond laboratory performance toward solutions that are adaptable, efficient, and explainable in field settings. Looking forward, the integration of lightweight and transformer-enhanced CNNs, coupled with diverse field datasets and deployment-ready optimizations, will be central to advancing tomato disease detection systems. Ultimately, these innovations have the potential to transform plant health monitoring, strengthen precision agriculture, and improve food security worldwide.

Abbreviations

Table 8: List of Abbreviations and Meanings

Abbreviations	Meaning
CapsNet	Capsule Networks
CNNs	Convolutional Neural Networks
DCNNs	Deep Convolutional Neural Networks
DenseNet	Densely Connected Convolutional Network (e.g., DenseNet-201)
DL	Deep Learning
GANs	Generative Adversarial Networks
IoT	Internet of Things
Map	Mean Average Precision
ResNet	Residual Network (e.g., ResNet50)
RQ	Research Question
SLR	Systematic Literature Review
SMOTE	Synthetic Minority Over-sampling Technique
VGG	Visual Geometry Group (e.g., VGG16, VGG19)
YOLO	You Only Look Once (e.g., YOLOX-S, YOLOv7)

Declarations

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Authors Contributions

All Authors contribute equally to this paper

Conflict of Interest

None

Availability of Data and Materials

All data (papers) analyzed are included in IEEE Xplore, ScienceDirect, Semantic Scholar, Springer, ResearchGate, and MDPI

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Figures

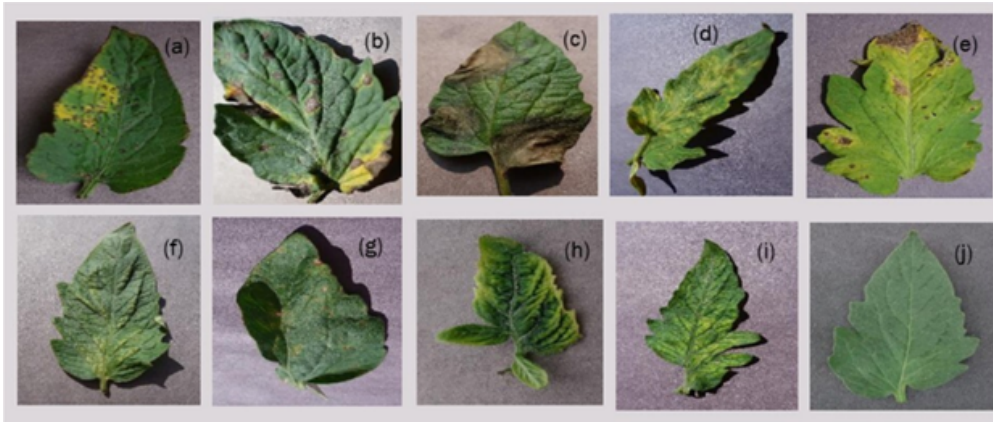


Figure 1

Pictorial View of the Tomato Leaf Disease

Two Spotted Spider Mite, Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Target Spot, Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, and Healthy