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Tomato Leaf Disease Recognition and Classification: A Review of Deep Learning Approaches, Challenges, and Future Directions.

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Abstract

Leaves are the most important components of plant life, which synthesize vital contents through photosynthesis. If leaves become sick from bacteria or other pathogens, the sickness may cause the yield of a crop to decline severely. That's why timely detection and precise identification of leaf diseases is so important for maintaining plant health. With the rapid advancement of deep learning technologies, we currently have efficient and reliable approaches that enable accurate recognition and classification, helping farmers take timely action to save their crops.

Keywords – CNN, Machine Learning, Deep Learning, Tomato Leaf disease

I INTRODUCTION:

Agriculture depends greatly on timely and accurate plant disease diagnosis to maximize crop yields, minimize food losses, and reduce reliance on chemical pesticides. Tomatoes rank among the most vital crops globally and draw significant public and agricultural interest. In 2020 alone, global tomato production reached around 130 million metric tons. Ensuring high-quality yield and improving harvests are key goals in modern agriculture.

Tomato, a common crop in the world, plays a key factor in maintaining food security and is among the most significant and most grown to economic, social and nutritional value. But it does prove somewhat susceptible to certain leaf diseases, such as Early Blight, late blight, bacterial spot, Yellow Leaf Curl and Septoria Leaf Spots [1]. If not recognized and managed on time, these diseases pose great threats to crop yield, product quality, and household income of the small holder farmers. Manual inspection has historically been the primary method for disease identification, though it tends to be labour-intensive, error-prone; and not conducive to industrial farming. Consequently, the demand for automated, efficient and scalable approaches to assist farmers in attending the issue has increased in these years.

Recent developments in artificial intelligence in particular in deep learning (DL) and machine learning (ML) have resulting in the emergence of accurate image-based systems for plant disease detection. Numerous studies have focused on the classification of tomato leaves diseases by using Convolutional Neural CNN) based networks, different versions of MobileNet models, Capsule Networks and Transformer models. For example, the Wave Shift Augmentation method and Modified MobileNetV3 [2] models have attention mechanisms. mechanisms and residual blocks in order to improve feature extraction, especially fine-grained disease classification tasks. For enhancing detection performance in the case of challenging visual scenarios, some methods like the TDR-Model employ with v3 (dehazing preprocessing techniques [3] with enhanced MobileNetV3architectures.) On the other hand, hybrid models, including Capsule Networks or Self-Guided Transformers [4] (mentioned in papers on CSGT and SE-SK-CapResNet) show the better performance in local and global leaf features. These models usually exceed standard CNNs by solving problems such as background noise and gradient normalization, complicated visual structures based on real-field images. Furthermore, real-time processing is attainable in models such as EfficientNet [5] & YOLOv7 [6].

In addition to model design, dataset development significantly contributes to improving the generalization of detection systems. Apart from model design, the creation of dataset is also crucial to boost the generalization of detection systems. Several such datasets like FieldPlant [7], Tomato Leaf Dataset [8], PlantVillage [9, 10] are popular for training and testing requirements and benchmark, however they are often held in a controlled manner. Addressing this shortcoming, certain studies have introduced custom or synthetic datasets and employed data augmentation techniques [11, 12] to simulate field conditions such as blur, varying brightness, and occlusion. Even with all this work, still remains a significant gap in the availability of diverse, real-world datasets that represent various geographic, climatic, and device-level conditions encountered by farmers.

While the surveyed models demonstrate high accuracy often exceeding 95% they also share common limitations. Many are not tested on noisy or low-resolution images, lack support for multi-label classification (where a leaf may show symptoms of more than one disease), and are not optimized for edge computing or real-time deployment. Moreover, few studies explore the integration of these models into Internet of Things (IoT) frameworks or mobile applications, limiting their practical value for smallholder farmers and large-scale agricultural monitoring systems. Therefore, it requires a strong need for future research to focus on lightweight model design, real-field validation, interpretability, and multi-disease detection capabilities.

In conclusion, detection of diseases in tomato leaves using deep neural networks and image processing has demonstrated meaningful progress with numerous innovative models and methodologies proposed in recent years. However, real-world applicability remains a challenge due to limitations in dataset diversity, model complexity, and deployment readiness. This survey aims to provide a comprehensive overview of these advancements, analyze current gaps, and suggest what we can do further for building robust, interpretable, and scalable detection models tailored for modern precision agriculture.

Numerous forms of diseases to tomato leaves be affected caused by fungi, bacteria, and viruses. Among the fungal infections, early blight, late blight, leaf mold, and Septoria leaf spot are commonly observed. Bacterial infections like bacterial spot, speck, and canker also pose serious threats to tomato foliage. In addition, viral diseases such as tomato mosaic virus and tomato spotted wilt virus often lead to visible symptoms on the leaves.

1. **Yellow Leaf Curl**

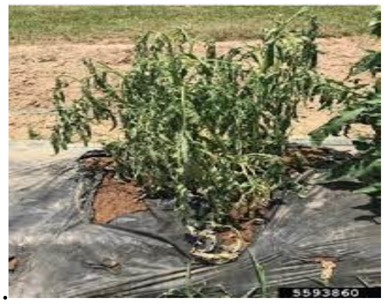
Symptoms: The leaves may become yellow, small and curling upward over time.

2. **Bacterial Spot**

   Symptoms: A small brown spots on leaves with yellow ring around them. These spots will fall away and leaves holes behind.

3. **Bacterial Wilt**

   Symptoms: The leaves may start to dry out and slowly change to yellow or brown, leading to the plant death.



4. **Mosaic Virus**

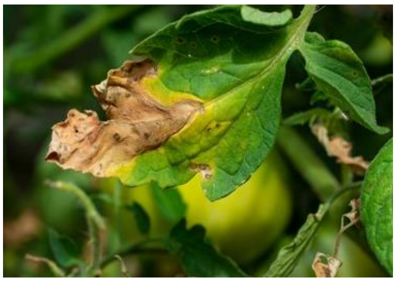
   Symptoms: Leaves may curl and develop a patchy and uneven coloration. New leaflets often appear smaller than normal.

5. **Leaf Mold**

Symptoms: This disease starts as light green or yellow spots on the upper surface of the leaves.

6. **Late Blight**

Symptoms: In damp conditions, a white mold ring can form around the affected areas and leaves may show greenish- gray, greasy edges. These spots will dry out over time and take on a thin and papery texture.



7. **Gray Leaf Spot**

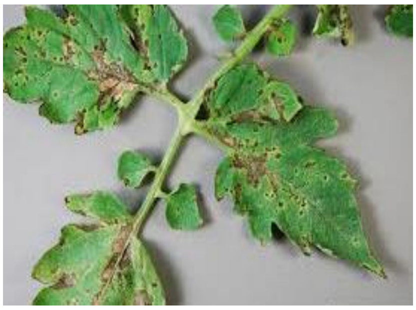
Symptoms: On the both upper and lower leave surface a tiny dark spots with yellow halos started to form. Spots become grayish-brown as they grow and fall away.

8. **Bacterial Speck**

Symptoms: uneven small brown to black spots near the leave edges, often surrounded by yellowing tissue.

9. Septoria Leaf Spot

Symptoms: It shows up as numerous small, dark spots on the leaves. These spots often develop pale tan or gray centres. Affected leaves wilt and drop as the disease progresses.



10. Powdery Mildew

Symptoms: Leaves develop yellow spots that gradually transform into white, powdery patches, eventually covering the entire leaf surface and spreading to the stems as well.

11. Fusarium or Verticillium Wilt

Symptoms: In warm conditions, the whole plant may droop during the day but often regains its firmness overnight. Symptoms typically begin on the older, lower leaves and progress upward. Over time, leaves on one side of the plant may yellow, dry out, turn brown, and drop off.

12. Early Blight

Symptoms: Dark brown spots with concentric ring patterns first appear on the lower leaves and gradually spread upward, leading to the leaves shriveling, drying out, and eventually dropping off.

II RELATED LITERATURE:

Here is the table showing the different models developed by authors in recent 3 (2023-25) years. In most of the papers author have used already existing datasets like Plant Village Dataset, CCMT dataset, Tomato leaf dataset etc. Accuracy in classifying the diseases is greater than 95% and each paper has its strengths and drawbacks also.

Table 1: Comparison and Summary of related work:

SL. No	Author and Year	Title	Techniques Used	Crops Taken	Data set	Performance				Advantage	Future Perspective (drawbacks)
						Accuracy	Precision	Recall	F1-score		
1.	Rubina Rashid(March 2025)	A Modified Mobile Netv3 Coupled With Inverted Residual and Channel Attention Mechanisms for Detection of Tomato Leaf Diseases	A lightweight, mobile-optimized CNN model	Tomato	Plant Village dataset	98.77% training accuracy	99%	99%	99%	1. Light weight model, designed for android. So farmers can use it for practical purpose. 3.Effective Feature Utilization 4.Computational Efficiency	1.Multi-Crop Support 2.Real-Time Field Testing in natural lighting and background Use real world field images to improve generalizability 4.Model Compression Techniques without compromising performance
2.	Ritesh Maurya (April 2025)	RAI-Net: Tomato Plant Disease Classification Using Residual-Attention-Inception Network	Deep learning-based hybrid model called RAI-Net	Tomato	Plant Village dataset	97.88%	-	-	-	Relatively lightweight, making the model feasible for deployment on mobile devices. The model focuses on important features only.	Data augmentation strategies to simulate real-world noise (shadows, brightness, rotations). Limits the practical deployment of the model in real-world agricultural applications.
3.	Tongliu(Jan 2025)	TDR-Model: Tomato Disease Recognition Based on Image Dehazing and Improved MobileNetV3 Model	Image Dehazing and Improved MobileNetV3 Model	Tomato	Public Dataset avalable on Kaggle and 100 synthetic hazy images	98.89% over clear images	-	-	98.93%	Lightweight and Efficient, Targets foggy conditions in greenhouse environments, which most models ignore. Significant Accuracy Boost foggy images	Enhance generalization to diverse real-world conditions. Embed the model into detection frameworks like YOLO for real-time crop monitoring. lack of field testing Complex pre-processing Fog specific

4.	R. Karthik (October 2024)	A Deep Learning Approach for Crop Disease and Pest Classification Using Swin Transformer and Dual-Attention Multi-Scale Fusion Network	Feature fusion-based deep learning model using a dual-track architecture	Cashew, Cassava, Tomayo and Maize	CCMT Dataset	95.68%	95.68%	95.68%	95.67%	Combines local and global feature learning for enhanced accuracy. High Accuracy on CCMT Dataset the architecture is adaptable for other plant diseases,	High Computational Complexity Real-World performance under uncontrolled condition isn't discussed. No Real-Time Testing or Field Validation:
5.	Xin Zhang (March 2024)	A Plant Leaf Disease Image Classification Method Integrating Capsule Network and Residual Network	Hybrid deep learning model called SE-SK-CapResNet	Potato ,Tomato, Corn, Apple	1.Plant Village 2.AI Challenger 2018 3.Tomato Leaf Disease dataset	98.58% 95.08% 97.19%	98.58%	98.58%	98.58%	Improved Feature Extraction Multi-dataset testing	Model complexity high Generalization to new crops untested Field validation absent Data set taken in controlled environments with clear background.
6.	Zhichao Chen (March 2024)	Using a Hybrid Convolutional Neural Network with a Transformer Model for Tomato Leaf Disease Detection	CycleGAN and a Transformer-Dense CNN	Tomato	1.AI Challenger 2018 2. Private Tomato Leaf Disease dataset	98.30% 95.4%	97%	98%	97%	Enhanced Feature Extraction High Accuracy Generalization	Lack of Real-World Testing Include early, mid, and late-stage disease data Optimize for edge/mobile deployment Private Dataset Not Publicly Available
7.	Anita Shrotriya (September 2024)	An Approach Toward Classifying Plant-Leaf Diseases and Comparisons With the Conventional Classification	clustering methods and neural networks	Few diseases. Crop not mentioned	Not Mentioned	96–97%.	-	-	-	Use of Traditional Yet Efficient Algorithms Clustering-Based Pre-processing leading to more precise feature extraction for classifiers: This model also calculates disease severity	Needs support for multiple diseases Generalization Model is not optimized for field use.

8.	Selvarajah Thuseethan December 2024	Siamese Network-Based Lightweight Framework for Tomato Leaf Disease Recognition	Siamese Network-based Lightweight Framework	Tomato	PlantVillage Dataset Taiwan Tomato Leaf Disease Dataset	96.97% 95.48%	-	-	-	Fast and memory-efficient Lightweight Lower computation time	The current model focuses on single-disease classification Evaluation on Real-World Data generalization untested
9.	Huinian Li (November 2024)	Convolution Self-Guided Transformer for Diagnosis and Recognition of Crop Disease in Different Environments	CNN Self-Guided Transformer and Hybrid-scale and attention mechanism	Apple corn grape tomato rice	Jiangsu Dataset(controlled) Guangdong Dataset(uncontrolled) – field images	96.9% 95.8% 96.1% 96.5% 95.8%	-	-	96.5 %	Scalable to Multiple Crops Robust to Complex Backgrounds	Multi-Disease and Multi-Label Classification Cross-Region Generalization Real-World Deployment Computational Complexity
10.	Jing Feng (March 2024)	Enhanced Crop Disease Detection With Efficient Net Convolutional Group-Wise Transformer	EfficientNet Convolutional Group-Wise Transformer	Tomato, Cassava	Cassava	86.9%	87.0 %	87.0 %	87.0 %	Reduces computational overhead Performs well across different crops	Performance Drop on Complex Datasets No On-Device Validation Limited Dataset Diversity
11.	M.H. Alnamoly (May 2024)	FL-ToLeD: An Improved Lightweight Attention Convolutional Neural Network Model for Tomato Leaf Diseases Classification for Low-End Devices	Lightweight CNN with Attention and DSC	Tomato	PlantVillage	98.04%	98%	98%	98%	Reduces model complexity and number of parameters Can be deployed on low-end smartphones	Limited Dataset Scope Overfitting Risk No Mention of Field Testing No Multi-Crop or Multi-Disease Capability

12.	Abdelmalik (Novenber 2024)	Knowledge Pre-Trained CNN-Based Tensor Subspace Learning for Tomato Leaf Diseases Detection	Higher-Order Whitened Singular Value Decomposition	Tomato	PlantVillage Dataset Taiwan Dataset	98.51% 89.49%	-	-	-	Better feature extraction. Performs well even on real-world data	computationally expensive Limited Deployment Suitability Dataset Diversity
13.	Muhammad umar (April 2024)	Precision Agriculture Through Deep Learning: Tomato Plant Multiple Diseases Recognition With CNN and Improved YOLOv7	CNN and Improved YOLOv7	Tomato	University Greenhouse (In-house Dataset)	98.8%	-	-	-	Field-Oriented Dataset Effective Augmentation Strategy	Limited Dataset Diversity Increased Model Complexity Not Real-Time Tested No Cross-Crop or Cross-Domain Testing
14.	Emmanuel (April 2023)	FieldPlant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learnin g	A new dataset named FieldPlant with deep learnin g		PlantVillage PlantDoc FieldPlant (Proposed)	-	-	-	-	Real-world data	Model still underperform overall on field ima Limited disease classes Limit deployment on mobile devices
15.	Khalid M. Hosny (June 2023)	Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern	lightweight Convolutional Neural Network	Apple, Tomato and Grape	Apple Leaf Dataset Tomato Leaf Dataset Grape Leaf Dataset	96-99%	96.0 %	96.0 %	96.0 %	Lightweight Architecture Cross-Dataset Testing Early Detection Support	No Field Image Testing Limited Disease Coverage May not capture complex patterns

16.	Hasibul (September 2023)	Plant Disease Classifier: Detection of Dual-Crop Diseases Using Lightweight 2D CNN Architecture	Custom Lightweight 2D CNN Architecture	tomato and cotton	PlantVillage Custom/ lab-annotated images for co	97.36%	97%	97%	97%	Small model size Near real-time disease classification	Limited Crop Variety No field validation
17.	Diana Susan Joseph (Feb 2024)	Real-Time Plant Disease Dataset Development and Detection of Plant Disease Using Deep Learning	Custom CNN	Rice Wheat and maize	Custom-created images	97.04% 97.06% 98.08%	-	-	-	Custom Dataset Creation Realistic Disease Classes	Lack of Field Validation Small original dataset Limited Disease Variety Environmental Variation Not Fully Captured
18.	R. Satya Rajendra Singh (Decenber 2023)	Zero-Shot Transfer Learning Framework for Plant Leaf Disease Classification	deep CNN architectures + Data Augmentation	Tomato potato	PlantVillage Data set	-	-	-	-	Generalizes to Unseen Data Reduces Need for Labeled Data	lacks numerical performance data (Accuracy) Assumes Quality of Synthetic Data ZSTL Still Emerging in Agriculture

III SUMMARY OF THE LITERATURE SURVEY:

This comprehensive table offers a comparative overview of recent deep learning-based methods for plant leaf disease detection, with a focus on tomato and other widely cultivated crops like potato, maize, rice, apple, and cassava. Most studies leverage convolutional neural networks (CNNs), often in combination with advanced mechanisms like attention modules, transformers [13], or hybrid architectures (e.g., MobileNetV3, YOLOv7, EfficientNet). Tomato is the most extensively studied crop across the papers, often using the PlantVillage dataset due to its popularity and availability. Many models demonstrate impressively high accuracy frequently exceeding 95%—especially in controlled environments [14]. Lightweight architectures, such as MobileNet variants and custom CNNs, are gaining attraction due to their suitability for deployment on mobile devices in agricultural settings.

In the paper [15, 16] methods used are giving good accuracy, performs well on real world data but limits in field validation, limited crop variety and computationally expensive. The model [17] calculates disease severity which is not done in most of the papers but the Model is not optimized for field use and not generalized to other crops and variety of diseases on the same crop. In most of the papers already existing datasets have taken but in this model [18] custom dataset is created but the size of the dataset is very small with limited disease variety. Also here environmental variation is not fully captured and model is not tested on filed.

Model RAI-Net [19] has achieved high accuracy by incorporating attention mechanisms, effective feature selection, and compact architectures optimized for efficient deployment on mobile devices.

However, several limitations emerge across studies. First, real-world validation is often missing—many datasets are captured under lab-controlled conditions with clean backgrounds, which fail to reflect field variability like lighting, occlusion, or background clutter. Models like the TDR-Model or the FL-ToLeD [20] show promise under synthetic or enhanced conditions (e.g., foggy greenhouse environments or for low-end smartphones), but generalization in natural farm conditions is rarely tested. Moreover, while some papers explore multi-crop or multi-disease classification, others remain limited to single-crop/single-disease frameworks. Additionally, despite high accuracy, computational complexity, dataset bias, and lack of cross-regional validation limit practical deployment. The future direction clearly calls for real-time testing, cross-domain generalization, multi-crop adaptation, and field-image-based learning to ensure robustness and usability in real agricultural environments.

IV CONCLUSION:

According to the survey of papers published recently in last 3 years, Deep Learning models are giving best accuracy in tomato leaf disease detection and classification. Few models are giving best accuracy such as Modified MobileNetV3, TDR-Model, Hybrid Deep Learning Model and CNN with Improved YOLOv7. One or two Light weight CNN models are also developed for mobile deployment. Even though the accuracy is good the models still facing problems like high computational complexity, model generalization, multi-label classification, multi-disease detection and lack of validation in real world environment.

V FUTURE WORK:

Despite authors have proposed so many significant methods to detect and classify diseases of tomato leaves, several critical future gaps remain. Many existing models are trained and tested on controlled or existing datasets, lacking real-world validation. And many authors not considered low-resolution images, environmental noise, images with complex background into account. In the filed environment practical usage of the models restricted because of developed high computational complexity, lack of model compression, and insufficient optimization for mobile or edge deployment.

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References

[1] Özbılge, Emre, et al. "Tomato disease recognition using a compact convolutional neural network." IEEE Access 10 (2022): 77213-77224.

[2] Rashid, Rubina, et al. "A Modified MobileNetv3 Coupled With Inverted Residual and Channel Attention Mechanisms for Detection of Tomato Leaf Diseases." IEEE Access (2025).

[3] Zhang, Zhixiang, et al. "TDR-Model: Tomato Disease Recognition Based on Image Dehazing and Improved MobileNetV3 Model." IEEE Access (2024).

[4] Li, Huinian, et al. "Convolution Self-Guided Transformer for Diagnosis and Recognition of Crop Disease in Different Environments." IEEE Access (2024).

[5] Feng, Jing, et al. "Enhanced crop disease detection with EfficientNet convolutional group-wise transformer." IEEE Access 12 (2024): 44147-44162.

[6] Umar, Muhammad, et al. "Precision agriculture through deep learning: Tomato plant multiple diseases recognition with cnn and improved yolov7." IEEE Access (2024).

[7] Moupojou, Emmanuel, et al. "FieldPlant: A dataset of field plant images for plant disease detection and classification with deep learning." IEEE Access 11 (2023): 35398-35410.

[8] Hosny, Khalid M., et al. "Multi-class classification of plant leaf diseases using feature fusion of deep convolutional neural network and local binary pattern." IEEE Access 11 (2023): 62307-62317.

[9] Zhang, Xin, et al. "A plant leaf disease image classification method integrating capsule network and residual network." IEEE Access (2024).

[10] Thuseethan, Selvarajah, et al. "Siamese network-based lightweight framework for tomato leaf disease recognition." Computers 13.12 (2024): 323.

[11] Singh, R. Satya Rajendra, and Rakesh Kumar Sanodiya. "Zero-shot transfer learning framework for plant leaf disease classification." IEEE Access 11 (2023): 143861-143880.

[12] Roy, Kyamelia, et al. "Detection of tomato leaf diseases for agro-based industries using novel PCA DeepNet." Ieee Access 11 (2023): 14983-15001.

[13] Chen, Zhichao, et al. "Using a hybrid convolutional neural network with a transformer model for tomato leaf disease detection." Agronomy 14.4 (2024): 673.

[14] Karthik, R., et al. "A Deep Learning Approach for Crop Disease and Pest Classification using Swin Transformer and Dual-Attention Multi-scale Fusion Network." IEEE Access (2024).

[15] Ouamane, Abdelmalik, et al. "Novel Knowledge Pre-trained CNN based Tensor Subspace Learning for Tomato Leaf Diseases Detection." IEEE Access (2024).

[16] Peyal, Hasibul Islam, et al. "Plant disease classifier: Detection of dual-crop diseases using lightweight 2d cnn architecture." IEEE Access 11 (2023): 110627-110643.

[17] Shrotriya, Anita, et al. "An Approach Towards Classifying Plant-Leaf Diseases and Comparisons with the Conventional Classification." IEEE Access (2024).

[18] Joseph, Diana Susan, Pranav M. Pawar, and Kaustubh Chakradeo. "Real-time plant disease dataset development and detection of plant disease using deep learning." Ieee Access 12 (2024): 16310-16333.

[19] Maurya, Ritesh, Lucky Rajput, and Satyajit Mohapatra. "RAI-Net: Tomato Plant Disease Classification Using Residual-Attention-Inception Network." IEEE Access (2025).

[20] Alnamoly, Mahmoud H., et al. "FL-ToLeD: An improved lightweight attention convolutional neural network model for tomato leaf diseases classification for low-end devices." IEEE Access (2024).