A Comprehensive Study on Tomato Leaf Disease and its Approaches

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***Abstract*—One of the most extensively cultivated and commercially important crops in the world is the tomato. However, a variety of illnesses, especially those that harm the leaves, significantly reduce its productivity. The purpose of this survey is to assess the frequency, seriousness, and management approaches of several tomato leaf diseases in various agricultural contexts. The study finds the most prevalent leaf diseases, such as Septoria Leaf Spot, Early Bligh, Late Blight, Bacterial Spot, Two Spotted Spider mite and Leaf Mold, through field observations and interviews with nearby farmers. The survey also evaluates how these illnesses affect crop quality and output, emphasizing the financial losses that farmers experience. By encouraging the creation of more resilient tomato cultivars and offering insightful information on sustainable disease management techniques, the results hope to improve tomato output and food security in the long run.**

***Index Terms*—IoT, Machine Learning, Smart Agriculture, Tomato Leaf Disease**

I. INTRODUCTION

Agriculture plays a pivotal role in sustaining economies and livelihoods, particularly in rural areas. However, traditional farming methods often face significant challenges such as crop diseases, inefficient irrigation, and over-reliance on middlemen, all of which negatively impact harvests and farmers' financial stability. These issues often lead to low profitability and poor resource allocation, affecting the overall success of farming operations. In recent years, digital technologies—particularly the Internet of Things (IoT) and Machine Learning (ML)—have revolutionized the agriculture sector, offering innovative solutions for precision farming. These technologies enable real-time crop monitoring, early disease detection, irrigation control, and data- driven decision-making, all of which contribute to enhanced productivity and environmental sustainability. Through smart sensors, data analysis, and remote control, farmers are equipped to make informed decisions that boost crop yields while minimizing resource waste. This paper presents a comprehensive smart farming system designed to address key agricultural challenges using IoT and ML, specifically tailored for tomato cultivation. The system integrates multiple components: image- based ML processing for disease detection, intelligent pesticide recommendation, and real-time smart irrigation. The central processing unit, an ESP32-WROOM microcontroller, communicates with various sensors and a camera module to capture leaf images and monitor soil conditions. These images are processed by a trained ML model to identify diseases and recommend appropriate pesticides. Sensor data, including soil moisture, temperature, and humidity, is continuously streamed to the ThingSpeak IoT platform, providing farmers with real-time updates and analysis. The integrated system improves agricultural efficiency, sustainability, and decision-making, empowering farmers to manage crop health more effectively. This paper highlights the design and implementation of the proposed system,

showcasing its potential to transform traditional farming practices into a smarter, more sustainable, and economically viable activity.

Tomato crops, in particular, are highly susceptible to a range of diseases that can severely reduce productivity. According to the Food and Agriculture Organization (FAO), crop diseases result in significant

losses, with tomato plants being particularly vulnerable to infectious bacteria, fungi, and viruses. Early detection of these diseases is crucial for minimizing losses and ensuring optimal growth, further underscoring the importance of integrating technology into agriculture for improved disease management and overall crop health.

II. LITERATURE REVIEW & KEY FINDINGS

#	Paper Title	Year	Methodology Used	Findings
1.	Plant Disease Detection and Pesticide Recommendation Using Deep Learning IEEE	2024	Convolutional Neural Network (CNN)	Pros:High accuracy (96%) for identifying plant diseases. Cons:Requires significant computational resources for deep learning model training.
2.	Development of Pest Detection and Pesticide Recommendation System in Leaf Images IEEE	2024	Convolutional Neural Network (CNN) with YOLO (You Only Look Once) algorithm	Pros:Enhances crop health and productivity by enabling early detection and intervention. Cons:The system's success depends heavily on a well-labeled dataset, which may not represent all real-world pest scenarios.
3.	Pesticide Recommender System for Detecting the Paddy Crop Diseases through SVM. IEEE	2024	Support Vector Machine (SVM)	Pros:SVM is known for its effectiveness in classification tasks, providing accurate disease detection. Cons:The model may not detect new or rare diseases if they were not part of the training dataset.
4.	Integrating Smart Farming with AI Techniques for Crop Disease Prediction. IEEE	2024	Convolutional Neural Networks (CNNs)	Pros:AI-driven models can predict diseases at an early stage, allowing farmers to take preventive measures. Cons:The accuracy of AI models depends on high- quality and comprehensive data, which may be hard to collect.
5.	Advances and Challenges in Computer Vision for Image-Based Plant Disease Detection: A Comprehensive Survey of Machine and Deep Learning Approaches. IEEE 2024	2024	Machine Learning: SVM, RF, KNN2. Deep Learning: CNN, RNN, LSTM, ResNet, VGG, Inception, YOLO	Pros:Machine learning and deep learning models, especially CNNs, have shown high accuracy in plant disease classification Cons:High-quality labeled datasets are essential for training models, but they are often difficult to obtain due to the complexity of capturing various diseases under different environmental conditions
6.	Deep Learning-Based Tomato Disease Detection for Smart Agriculture. IEEE	2024	Machine Learning: RF, SVM, KNN- Deep Learning: CNN, RNN, LSTM	Pros:Deep learning models, especially CNNs, are highly accurate in detecting and classifying plant diseases from images. Cons:The model requires a large, high-quality labeled dataset to train effectively, which may not always be available
7.	CROPCARE: An Intelligent Real-Time Sustainable IoT System for Crop Disease Detection Using Mobile Vision. IEEE	2023	Convolutional Neural Network (CNN)	Pros:Enables farmers to monitor crops continuously and take prompt action on disease outbreaks. Cons:The storage and transfer of agricultural data may pose security risks if not managed correctly.
8.	Plant Disease Severity Detection and Fertilizer Recommendation using Deep Learning	2023	Convolutional Neural Network (CNN) with ResNet50 architecture	Pros:Increased crop yields Cons:May not work well with unusual or unknown diseases.

	Techniques IEEE			
9.	Smart Farming Using Machine Learning and Deep Learning: A Review. IEEE	2023	Machine Learning: Random Forest, SVM, KNN- Deep Learning: CNN, RNN, LSTM	Pros:ML and DL techniques can provide high accuracy in predicting crop diseases, pest attacks, and yield forecasts. Cons:The performance of ML and DL models heavily relies on high-quality, labeled data, which may be difficult to collect, especially in rural areas.
10.	Leaf Diseases Prediction Pest Detection a nd Pesticides Recommend ation u sing Deep Learning Techniques IEEE	2023	MFL-DCNN (Multi-dimensional Feature Learning-based Deep Convolutional Neural Network)	Pros:Automates disease detection, saving time and effort for farmers. Cons:Requires a large and diverse dataset for accurate predictions.
11.	Plant Disease Classificatio n and Identificatio n Using Deep Convolution al Neural Network IEEE	2023	AlexNet-based Convolutional Neural Network (CNN)	Pros:Simplifies disease detection through a smartphone application, making it accessible to farmers. Cons:Relies on a limited dataset of specific crops (tomatoes), which may not generalize well to other plants or diseases.
12.	Image-based Plant Diseases Detection using Deep Learning.	2023	Convolutional Neural Networks (CNN)- AlexNet- VGG16- ResNet50	Pros:CNN-based models often achieve high accuracy in plant disease detection, outpacing traditional methods by being able to discern subtle visual patterns that humans may overlook. Cons:Deep learning models require large volumes of labeled data to train effectively.
13.	Plant Disease Detection and Classificatio n by Deep Learning—A Review.	2021	CNN- DNN- Transfer Learning- RNN- LSTM- AlexNet- VGG16- ResNet50	Pros:Deep learning models, especially CNNs, have shown high accuracy in identifying plant diseases, outperforming traditional methods by automatically learning complex patterns in large datasets. Cons:Deep learning models require large, high- quality, labeled datasets for effective training
14.	Plant Disease Detection and Classificatio n by Deep Learning—A Review. IEEE	2021	Convolutional Neural Networks (CNN)- Transfer Learning (TL)- Recurrent Neural Networks (RNN)- Long Short-Term Memory (LSTM)	Pros:Deep learning models have demonstrated superior accuracy in plant disease detection compared to traditional methods, thanks to their ability to learn intricate patterns in large datasets. Cons:Deep learning models require large amounts of labeled data for training, and obtaining high-quality, labeled datasets for plant diseases can be difficult and time-consuming.

III. DISEASES IN TOMATO LEAF

Early Blight: This is also termed as Alternaria solani. Some of the common symptoms are Dark concentric rings found on older leaves, Yellowing lesions and affected leaves might die. These kinds of symptoms arises due to Fungal infection which would be worsened by wet, humid conditions. Some of the common treatment methods are avoid overhead watering, use of fungicides, and removal of infected leaves.

Spectorial leaf spot: The term provided does not correspond to a widely recognized or standardized plant disease name in scientific literature; however, it is likely a reference to Septoria leaf spot, a well-documented fungal disease affecting tomato plants. This disease is characterized by the appearance of small, circular to irregular brown or black lesions on

the leaves, often with grayish centers and dark margins. Effective management practices include cultural controls such as removing and destroying infected foliage, avoiding overhead irrigation to minimize leaf wetness, ensuring adequate plant spacing to promote air circulation, and practicing crop rotation by avoiding successive tomato plantings in the same location.

Late Blight: It caused by Phytophthora infestans, is a serious and fast-spreading disease in tomato plants. Symptoms typically begin as large, water-soaked lesions, often appearing at the edges or tips of leaves. These lesions progressively turn brown to black and are frequently surrounded by a pale green or yellow halo. Under humid conditions, a white, fuzzy fungal growth may be visible on the underside of affected leaves.Effective management includes the application of preventive fungicides, particularly during wet or humid weather. Recommended treatments include contact fungicides such as chlorothalonil, mancozeb, and copper-based formulations, as well as systemic options like metalaxyl or cymoxanil. Fungicides should be reapplied according to product label instructions, especially following rainfall, to maintain protection and limit disease spread.

Bacterial Spot : It is caused by Xanthomonas spp., is a common bacterial disease affecting tomato foliage. Initial symptoms appear as small, water-soaked lesions on the leaves, which gradually enlarge and turn dark brown to black. These spots are typically surrounded by distinctive yellow halos. Infected leaves may become distorted, torn, or crinkled, and often drop prematurely, leading to reduced plant vigor.Management relies primarily on preventive chemical control, as curative options are limited. Copper-based bactericides are commonly used, often in combination with mancozeb to enhance efficacy. Applications should begin early in the growing season and be repeated weekly, especially during periods of wet or humid weather, to suppress disease development and spread.

Two-Spotted Spider Mite: The two-spotted spider mite is a damaging pest that affects a wide range of plants. Initial symptoms include yellow or stippled spots on the leaves caused by feeding, which can lead to browning, drying, and eventual premature leaf drop. Infestations often result in a mottled or marbled leaf appearance and can significantly stunt plant growth if left unchecked. Fine, silken webbing may also be visible on the undersides of leaves or between stems. Effective treatment options include spraying insecticidal soap or neem oil to suffocate mites or disrupt their life cycle. Introducing predatory mites like Phytoseiulus persimilis provides natural biological control. Additional methods such as forceful water sprays, using miticides in severe cases, removing infested leaves, avoiding overhead watering, and increasing humidity can all help reduce mite populations and prevent further damage.

Leaf Mold: Leaf mold is a fungal disease that commonly affects tomatoes and other plants, typically starting with pale green or yellow spots on the upper leaf surfaces. These spots correspond to fuzzy gray, white, or olive mold that develops on the underside of the leaves. As the infection worsens, leaves may curl, wilt, become brittle, and eventually fall off, weakening the plant. Though it rarely affects fruit, severe cases can impact blossoms or fruit surfaces. Effective treatment includes removing infected leaves, improving air circulation by spacing and pruning, and watering at the base to keep foliage dry. In more serious infections, fungicides like chlorothalonil, copper-based sprays, or potassium bicarbonate can be applied. Maintaining proper sanitation and choosing resistant plant varieties also help prevent future outbreaks.

IV. APPROACHES

The existing system for tomato leaf disease detection and pesticide recommendation leverages advanced image processing and machine learning techniques to automatically identify and classify diseases affecting tomato plants. The core functionality is built around a Convolutional Neural Network (CNN), which processes high-resolution images of tomato leaves to detect various diseases with high accuracy. Once a disease is identified, the system provides tailored pesticide recommendations, including both chemical and organic solutions, accompanied by proper usage instructions, dosage, safety precautions, and preventive measures.

To build such systems, various technical methods can be employed:

1. Traditional Image Processing

Traditional image processing relies on handcrafted features and classical machine learning algorithms.

Feature Extraction Methods:

- Color Histogram: Represents the distribution of pixel intensities in an image.

Formula: $H(i) = n_i / N$

- Texture Analysis (GLCM): Extracts statistical texture features like contrast and homogeneity.

Contrast = $\Sigma(i - j)^2 * P(i, j)$

- Edge Detection (Sobel): Detects edges using gradients.

$G = \sqrt{(G_x^2 + G_y^2)}$

Classification Algorithms:

- SVM: Uses hyperplanes to separate classes.

$f(x) = \text{sign}(w^T x + b)$

- KNN: Classifies based on the majority of k nearest neighbors.

2. Deep Learning with CNNs

Convolutional Neural Networks (CNNs) automatically learn features from images through convolutional layers, pooling, and fully connected layers. Common architectures include VGG16, ResNet50, and MobileNet.

Convolution Operation (discrete 2D):

$S(i,j) = \Sigma_m \Sigma_n I(i-m, j-n) * K(m,n)$

Loss Function (Categorical Cross-Entropy):

$L = -\Sigma y_i \log(\hat{y}_i)$

3. Transfer Learning

Transfer learning involves using pre-trained models like EfficientNet or InceptionV3 and fine-tuning them on tomato leaf datasets. It reduces training time and improves performance on small datasets.

Example Keras code:

```
base_model = EfficientNetB0(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

x = GlobalAveragePooling2D()(base_model.output)

output = Dense(num_classes, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=output)
```

4. Ensemble Learning

Combines predictions from multiple models using methods like voting, stacking, or model averaging. Improves robustness and accuracy.

Soft Voting Formula:

$\hat{y} = \text{argmax}_j (1/M \Sigma p_j^{(m)})$

5. Edge Computing for Real-Time Diagnosis

Lightweight models such as MobileNet are deployed on edge devices (e.g., mobile phones, Raspberry Pi) to allow real-time, offline diagnosis in the field.

Model optimizations include quantization and conversion using TensorFlow Lite or ONNX.

6. IoT Integration

IoT devices integrate sensors (e.g., soil moisture, pH, temperature) with the disease detection system to support smart irrigation and targeted treatment.

Example: Low moisture + early blight detection → Recommend fungicide + irrigation.

7. Cloud-Based Systems

High-performance models are hosted on cloud platforms like AWS or GCP. Users upload images through a web/mobile app and receive instant disease diagnosis and treatment recommendations.

Latency:

Total Time = Upload Time + Inference Time + Response Time.

CONCLUSION AND FUTURE SCOPE

In this survey we have highlighted the integrated and sustainable management strategies are needed to fight tomato leaf diseases. Even while chemical control is still commonly used, using it excessively can have negative environmental effects, which is why creating eco-friendly alternatives is crucial. A better- informed agricultural community can drastically lower losses, which also emphasizes the importance of farmer education in managing and preventing illness. The major focus of this survey is to list on various types of diseases that arises in tomato crop and also various techniques used to detect the diseases in a crop at an early stage. Enhancing tomato cultivar resilience and investigating biocontrol techniques that complement sustainable farming methods should be the main goals of future research.

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