



Tomato Crop Disease Detection And Prescription Using CNN: Survey Paper

By: Rutvij Deo, Harshada Jadhav, Aditya Londhe & Bhushan Thombare

Abstract

India is the second largest producer of Tomato crops globally. Tomato crops are also cash crops for farmers in India and are extremely water intensive to grow and product. For most farmers many can't afford to let their current crops fall victim to diseases rendering such an intensive investment in failure. Timely detection and accurate diagnosis are essential to control the spread of these diseases and ensure optimal yields. In recent years, deep learning, especially Convolutional Neural Networks (CNNs), has emerged as a powerful tool for plant disease detection from images. This survey provides a detailed overview of CNN-based approaches for tomato crop disease detection, highlighting state-of-the-art techniques, datasets, and challenges. Additionally, it discusses the integration of a prescription system that aides farmers with timely interventions. The paper concludes by exploring the challenges and limitations.

1. Introduction

1.1 Background and Motivation

Tomatoes are among the most widely cultivated vegetables globally. However, their productivity is frequently hindered by diseases such as bacterial spots, late blight, and mosaic viruses. Traditional manual detection methods are time-consuming, prone to errors, and dependent on expert knowledge. With the rise of artificial intelligence, automated disease detection through deep learning offers a promising alternative.

Convolutional Neural Networks (CNNs) have gained popularity in computer vision for their ability to learn complex patterns from images. In agriculture, CNN-based models can classify plant diseases from leaf images with high accuracy[1]. Integrating these models with automated prescription systems can further enhance the decision-making process by recommending preventive or curative actions based on the identified disease.

1.2 Objectives of the Survey

- Provide a comprehensive overview of CNN architectures used for tomato disease detection.
- Review and analyze the key datasets available for plant disease classification.
- Identify research conducted up to date.

1.3 Organization of the Paper

This survey is structured as follows: Section 2 provides an overview of related work. Section 3 discusses CNN architectures and their applications in disease detection. Section 4 explores the design of disease detection and prescription systems. Section 4 highlights challenges and limitations. Section 5 presents future research directions. Finally, Section 6 concludes the paper.

2. Related Work on Crop Disease Detection

2.1 Overview of Image-based Detection Methods

Traditional plant disease detection relied on machine learning models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest classifiers. These methods require handcrafted feature extraction, which is laborious and often lacks the precision needed for large-scale deployments[2].

With the advent of deep learning, CNNs have demonstrated superior performance in image classification tasks[3]. Unlike traditional approaches, CNNs automatically learn features from raw images, making them more effective for complex visual patterns like disease symptoms on leaves.

There is also a potential of crop disease detection with the convenience of a smartphone for an immediate diagnosis.[4]

2.2 Review of Tomato Crop Disease Datasets

One of the most widely used datasets in plant disease detection is the **PlantVillage dataset**, which contains thousands of labeled images of healthy and diseased crops, including tomato plants. The dataset covers diseases such as:

- **Bacterial spot**
- **Late blight**
- **Leaf mold**
- **Tomato mosaic virus**

Data augmentation techniques like rotation, flipping, and scaling are often employed to increase the diversity of training data. However, dataset quality is crucial, as inconsistent lighting or background noise can reduce model accuracy.

3. CNN Architectures for Crop Disease Detection

3.1 Overview of CNN Models

Several CNN architectures have been used for tomato disease detection, including:

- **AlexNet**: One of the first deep networks, effective but computationally heavy.
- **VGGNet**: Deeper than AlexNet, providing better accuracy but requiring more training time.
- **ResNet**: Uses residual connections to address the vanishing gradient problem, making it highly effective for deeper networks.
- **MobileNet**: A lightweight CNN architecture ideal for real-time, mobile applications.

3.2 Techniques for Optimizing CNNs

- **Transfer Learning**: Pre-trained models (e.g., ResNet) are fine-tuned on plant datasets, reducing training time and improving performance.[5]
- **Data Augmentation**: Enhances generalizability by simulating real-world variations in the training dataset.
- **Hyperparameter Tuning**: Parameters such as learning rate, batch size, and number of epochs are carefully selected to optimize performance.

3.3 Performance Metrics

To evaluate CNN models, several performance metrics are used:

- **Accuracy:** Proportion of correct predictions.
- **Precision and Recall:** Measures of model reliability and sensitivity.
- **F1-score:** Harmonic mean of precision and recall.
- **Inference Time:** Time taken to make a prediction, which is critical for real-time applications.

4. Disease Detection and Prescription System Design

4.1 System Pipeline

A typical disease detection and prescription system involves:

1. **Image Acquisition:** Images are captured using smartphones, drones, or cameras installed in greenhouses.
2. **Preprocessing:** Images are resized, normalized, and augmented to enhance model performance.
3. **Disease Classification:** A trained CNN model predicts the disease label. This CNN can be trained on various types of data including historical prescriptions.[6]

4.2 Prescription Methods

After disease detection, a prescription system provides actionable recommendations, such as:

- Chemical treatments (fungicides, pesticides)
- Optimal irrigation schedules
- Suggestions for nutrient management and crop rotation

Integration with **weather forecasts** and **soil data** ensures that prescriptions are tailored to local conditions.

5. Challenges and Limitations

5.1 Complex real world factors

In the real world there are multiple factors at play. Some crops have multiple disease at the same time. Weather conditions, Soil conditions, implement types among others can also influence the health of a crop. Understanding these parameters beyond just an image will help better understand the problem's complexity.

5.2 Data Scarcity and Annotation Challenges

An AI model is as accurate as the data it is trained on. Finding the adequate amount of data to train is difficult to obtain and accrue.

5.3 Infrastructure and Deployment Constraints

Rural areas may lack the computational infrastructure needed for real-time CNN inference. Additionally, limited internet connectivity can hinder the use of cloud-based solutions.

6. Conclusion

This survey reviewed the state-of-the-art CNN-based approaches for tomato crop disease detection. While CNNs offer significant improvements over traditional methods, challenges related to data quality, model generalization, and deployment remain. The integration of prescription systems can transform disease detection systems into comprehensive decision-making tools for farmers.

7. References

- 1. Naresh K.Trivedi , Vinay Gautam, Abhineet Ananad, Hani Moaiteq Aljahdali, Santos Gracia Villar, Divya Anand, Nitin Goyal & Seifedine Kadry (2021). “Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network.” *Sensors* 2021, 21(23), 7987;
- 2. Mohit Agarwal , Suneet Kr. Gupta & K.K. Biswas (2020). “Development of Efficient CNN model for Tomato crop disease identification.” *Sustainable Computing: Informatics and Systems Volume 28, December 2020, 100407*
- 3. Alex Krizhevsky, Ilya Sutskever & Geoffrey E. Hinton (2012).”ImageNet Classification with Deep Convolutional Neural Networks.”
- 4. Sharada P. Mohanty, David P. Hughes & Marcel Salathe (2016).”Using Deep Learning for Image-Based Plant Disease Detection.” *Frontiers in Plant Science*, 7, 1419.
- 5. Kim, Sam-Keun & Ahn, Jae-Geun(2021).”Tomato Crop Diseases Classification Models Using Deep CNN-based Architectures.” *Journal of the Korea Academia-Industrial cooperation Society Volume 22 Issue 5 Pages.7-14 / 2021 / 1975-4701(pISSN) / 2288-4688(eISSN)*
- 6. Chang Xu , Junqi Ding, Yan Qiao & Lingxian Zhang(2022).”Tomato disease and pest diagnosis method based on the Stacking of prescription data.” *Computers and Electronics in Agriculture Volume 197, June 2022, 106997*

