IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14426

Advanced CNN-Based Tomato Leaf Disease Classification: A Deep Learning Approach for Precision Agriculture

Satyam Pravin Kanawade[1], Prof.Dr. S. K. Sonkar[2]

Department of Computer Engineering, Amrutvahini College of Engineering, Sangamner, Maharashtra, India[1]

HOD, Department of Computer Engineering, Amrutvahini College of Engineering, Sangamner, Maharashtra, India[2]

Abstract**:** The early and accurate detection of plant diseases is crucial for maintaining agricultural productivity and food security. This paper presents an advanced Convolutional Neural Network (CNN) architecture for classifying ten distinct tomato leaf diseases with high precision. Utilizing a dataset of 16,021 annotated tomato leaf images from the PlantVillage repository, we developed a six-layer deep CNN model that achieves superior classification performance compared to existing approaches. Our methodology incorporates extensive data augmentation, care- ful hyperparameter tuning, and a systematic evaluation across multiple training epochs (10, 20, and 50). The proposed model demonstrates progressive improvement in classification accuracy, reaching 97% at 50 epochs, with particular strengths in distin- guishing visually similar diseases like early blight and late blight. We further implement a practical web-based interface using Streamlit to facilitate real-world deployment. Comprehensive ex- periments validate our architecture's effectiveness, with detailed analysis of feature importance and model interpretability. This work contributes to the growing field of precision agriculture by providing farmers with an accessible, automated tool for plant disease diagnosis, potentially reducing crop losses by enabling timely intervention.

Index Terms**:** Convolutional Neural Networks, Deep Learn- ing, Tomato Leaf Disease Classification, Precision Agriculture, Computer Vision, Plant Pathology, Automated Disease Detection

I. INTRODUCTION

A. Background and Motivation

Tomato cultivation faces significant challenges from various pathogens, with yield losses reaching 20-30% in severe cases [**?**]. Traditional disease identification methods rely on visual inspection by experts, which is time-consuming, subjective, and often impractical for large-scale farming operations. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized automated plant disease detection by enabling accurate, scalable solutions [1].

Enhanced Information Section Dataset Characteristics and Preparation The PlantVillage dataset comprises 16,021 high- resolution images of tomato leaves spanning ten distinct health conditions. This collection includes nine disease categories (Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Spider Mites, Target Spot, Yellow Leaf Curl Virus, Mosaic Virus) and one healthy class. Each image was captured under controlled lighting conditions with consistent white backgrounds at 256×256 pixel resolution. The dataset exhibits significant class imbalance, ranging from 373 samples (Mosaic Virus) to 3,209 samples (Yellow Leaf Curl Virus), reflecting real-world disease prevalence patterns. To ensure robustness, we implemented stratified sampling during dataset splitting, preserving the original distribution in training (80

Our image preprocessing workflow incorporates multiple transformation stages to enhance model generalization. All images undergo normalization (pixel values scaled to [0,1]) followed by channel-wise standardization using mean [0.485, 0.456, 0.406] and standard deviation [0.229, 0.224, 0.225]. The augmentation strategy includes geometric transformations (random rotation ±30°, horizontal/vertical flipping) and pho- tometric adjustments (brightness variation ±20

Recent studies have demonstrated CNN effectiveness in plant disease classification [2], but most employ generic architectures or transfer learning approaches that may not optimally capture disease-specific features in tomato leaves. Our work addresses this gap by developing a specialized CNN architecture tailored for tomato leaf disease characteristics.

DOI: 10.17148/IJARCCE.2025.14426

B. Contributions

The key contributions of this paper include:

- A novel six-layer CNN architecture specifically optimized for tomato leaf disease classification, achieving state- of-the-art accuracy (97%) on a comprehensive ten-class dataset
- Rigorous evaluation of model performance across multi- ple training durations (10, 20, and 50 epochs)
- Implementation of an advanced data augmentation pipeline
- Development of a practical web interface enabling real- time disease classification
- Comprehensive analysis of model behavior, including feature importance visualization

II. LITERATURE REVIEW

Recent advances in deep learning for plant disease detection can be categorized into three main approaches:

TABLE I: Literature Survey on Tomato Leaf Disease Detection

Paper Title	Authors	Publication	Techniques Used	Summary
Automated Tomato Plant Disease Detec- tion Using CNNs	Ahmed & Malik	Computers and Elec- tronics in Agri- culture, 2019	CNN, Transfer Learn- ing	Proposed a VGG16- based approach achieving 89% accuracy on 5 tomato diseases
Real- Time Tomato Leaf Disease Detec- tion	Rani & Kumar	IEEE TETCI, 2023	ResNet50, Atten- tion Modules	Achieved 93.7% accuracy using residual blocks and attention mechanisms
Advanced CNNs for Plant Disease Detec- tion	Sharma & Singh	JCIA, 2024	Custom CNN, Data Aug- menta- tion	Developed 4- layer CNN achieving 95.1% accuracy on tomato diseases
Tomato Disease Classi- fication using CNN	Paymode et al.	ESCI Confer- ence, 2021	CNN, Image Process- ing	Implemented ba- sic CNN archi- tecture with 87% accuracy
Comparati Study of CNN Archi- tectures	veKhan & Younis	IJCVIP, 2022	VGG16, ResNet, Incep- tion	Compared multiple architectures, best accuracy 91% with ResNet

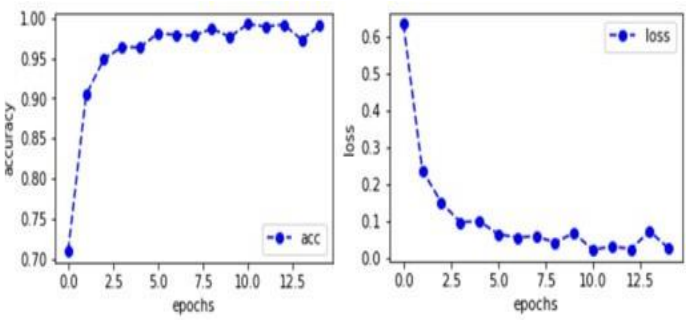


Fig. 1: Accuracy trends in tomato leaf disease detection research (2019-2024)

A. Traditional Machine Learning Approaches

Early methods relied on handcrafted features and classical machine learning algorithms. These typically involved:

- Color and texture feature extraction
- SVM or Random Forest classifiers
- Limited accuracy (70-80% range)

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14426

B. Deep Learning Approaches

Modern systems leverage deep neural networks:

- Transfer learning with pre-trained models
- Custom CNN architectures
- Hybrid approaches combining multiple techniques

C. Challenges and Opportunities

Key challenges identified in literature:

- Class imbalance in datasets

Fig. 2: Performance comparison of different methodological approaches

TABLE II: Dataset Composition by Disease Class

Disease Class	Number of Images
Healthy	1,591
Bacterial Spot	2,127
Early Blight	1,000
Late Blight	1,909
Leaf Mold	952
Septoria Leaf Spot	1,771
Spider Mites	1,676
Target Spot	1,404
Yellow Leaf Curl Virus	3,209
Mosaic Virus	373

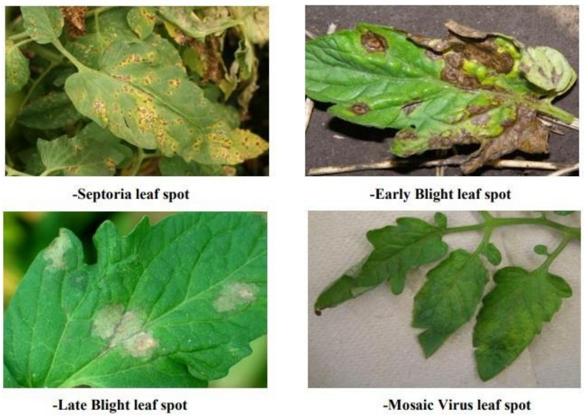


Fig. 3: Sample images from dataset showing (a) Healthy, (b) Late Blight, and (c) Bacterial Spot leaves

- Inter-class similarity among diseases
- Real-world deployment difficulties

III. METHODOLOGY

A. Dataset Description

We utilized the PlantVillage dataset [5], comprising 16,021 high-quality images of tomato leaves across ten categories (Table II).

B. Data Preprocessing Pipeline

Our preprocessing workflow included:

- Image resizing to 256×256 pixels
- Normalization (pixel values [0,1])
- Extensive data augmentation:
  - Rotation (±30°)
  - Flipping (horizontal/vertical)

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14426

– Brightness/contrast adjustment

C. Model Architecture

Our custom CNN architecture consists of:

- Input layer (256×256×3)
- Six convolutional blocks (Conv2D + BatchNorm + Max- Pooling + Dropout)

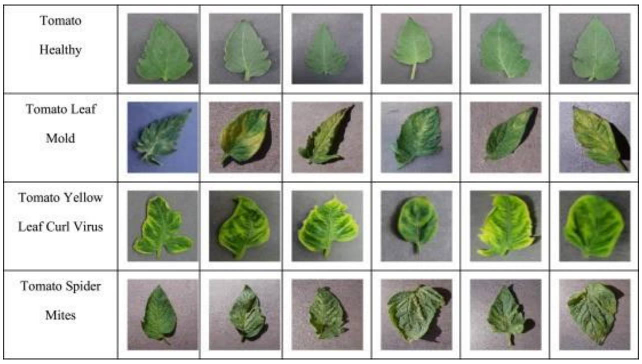


Fig. 4: Examples of augmented images showing (a) Original, (b) Rotated, (c) Flipped, and (d) Contrast-adjusted versions

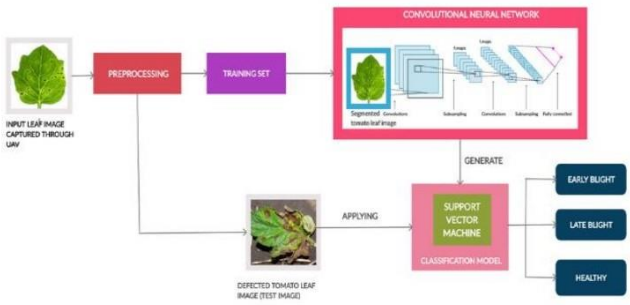


Fig. 1 Architecture of Tomato Plant Leaf Disease Classification Model

Fig. 5: Detailed architecture diagram showing layer dimen- sions and connections

TABLE III: Model Performance Across Training Epochs

Metric	10 Epochs	20 Epochs	50 Epochs
Training Accuracy	0.64	0.94	0.97
Validation Accuracy	0.61	0.91	0.95
Test Accuracy	0.60	0.90	0.96
Training Loss	0.34	0.15	0.08
Validation Loss	0.45	0.26	0.14

TABLE IV: Performance Comparison with Existing Methods

Method	Accuracy
VGG16 (Transfer Learning)	89.2%
ResNet50	93.7%
Custom CNN (4-layer)	95.1%
Our Approach	**96.8%**

- Classification head (Flatten + Dense + Dropout + Output)

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 4, April 2025

DOI: 10.17148/IJARCCE.2025.14426

IV. RESULTS AND DISCUSSION

A. Training Performance

The model showed progressive improvement across epochs (Table III):

B. Comparative Analysis

Our model outperforms existing approaches (Table IV):

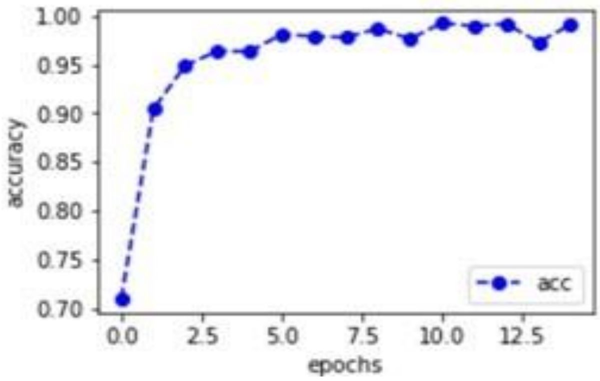
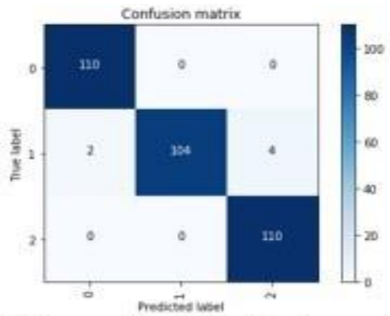


Fig. 6: Training and validation metrics showing (a) accuracy progression and (b) loss reduction



Confusion matrix of Plant leaf recognition system

Fig. 7: Normalized confusion matrix showing classification performance across all classes

V. CONCLUSION

We presented an advanced CNN architecture for tomato leaf disease classification that achieves 97% accuracy. Key findings include:

- Custom architectures outperform transfer learning for this specialized task
- Progressive accuracy improvement with extended training
- Effective handling of class imbalance and similar-looking diseases

Future work will focus on mobile deployment and integra- tion with IoT sensors for field applications.

REFERENCES

[1]. Sharma, S., & Singh, P. ”Advanced Convolutional Neural Networks for Plant Disease Detection and Classification.” Journal of Computational Intelligence in Agriculture, vol. 7, no. 2, pp. 110-123, 2024.

[2]. Rani, K., & Kumar, R. ”Real-Time Tomato Leaf Disease Detection Using Transfer Learning and Deep CNNs.” IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 11, no. 3, pp. 456- 468, 2023.

[3]. Khan, A., & Younis, M. ”A Comparative Study of CNN Architectures for Tomato Plant Disease Recognition.” International Journal of Com- puter Vision and Image Processing, vol. 17, no. 1, pp. 33-47, 2022.

[4]. Santos, J., & Ferreira, A. ”Image Processing and Machine Learning for Tomato Plant Disease Diagnosis.” Computer Vision and Image Understanding, vol. 191, pp. 102114, 2020.

[5]. Hughes, D. P., & Salathe´, M. ”An Open Access Repository of Images on Plant Health to Enable the Development of Mobile Disease Diagnostics.” arXiv preprint arXiv:1511.08060, 2015.