

Deep Learning-Based Crop Disease Detection Using Transfer Learning for Smart Agriculture

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Abstract - Agriculture remains a critical sector for global food security and economic stability. Crop diseases significantly reduce agricultural productivity, causing substantial economic losses worldwide. Traditional disease identification methods rely on manual inspection by experts, which is time-consuming, subjective, and often inaccurate. Recent advancements in Deep Learning (DL) and Computer Vision provide efficient automated solutions for plant disease detection. This paper proposes a deep learning-based crop disease detection system using transfer learning techniques. Pre-trained convolutional neural network (CNN) models such as ResNet50 and MobileNetV2 are fine-tuned using the PlantVillage dataset to classify healthy and diseased plant leaves. The proposed approach leverages transfer learning to reduce computational complexity and improve classification performance. Experimental results demonstrate that the ResNet50-based model achieves superior accuracy compared to baseline CNN models. The proposed system can assist farmers and agricultural stakeholders in early disease detection, thereby improving productivity and sustainability in smart agriculture systems.

Keywords—Deep Learning, Transfer Learning, Crop Disease Detection, Convolutional Neural Network, Smart Agriculture, Precision Farming.

1.Introduction

Agriculture contributes significantly to the GDP of many developing and developed countries. However, crop diseases remain one of the major threats to agricultural productivity. Early detection and diagnosis are essential to prevent large-scale crop damage.

Conventional disease detection methods involve manual field inspection, which requires domain expertise and is prone to human error. With the advancement of Artificial Intelligence (AI), particularly Deep Learning, image-based disease detection systems have gained attention.

Convolutional Neural Networks (CNNs) have demonstrated high performance in image classification tasks. Transfer learning allows leveraging pre-trained models trained on large

datasets such as ImageNet to improve performance on smaller agricultural datasets.

This research aims to develop a robust and accurate deep learning model using transfer learning techniques for automated crop disease detection.

Contributions of this Paper:

1. Development of a transfer learning-based crop disease classification model.
2. Comparative analysis of ResNet50 and MobileNetV2 architectures.
3. Performance evaluation using standard classification metrics.
4. Proposal of a scalable smart agriculture framework.

2. Literature Review

Several researchers have explored machine learning and deep learning techniques for crop disease detection.

Early approaches used traditional machine learning algorithms such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) with handcrafted features. However, these approaches required manual feature extraction.

Deep learning approaches, particularly CNNs, automatically extract hierarchical features from images and provide improved accuracy.

Recent studies have applied transfer learning using models such as:

- * VGG16
- * ResNet
- * InceptionNet
- * MobileNet

Transfer learning significantly reduces training time and improves generalization performance.

Despite promising results, challenges such as dataset imbalance, environmental variability, and real-time deployment remain open research problems.

3. Proposed Methodology

3.1 System Overview

The proposed system consists of the following stages:

1. Image Acquisition
2. Data Preprocessing
3. Feature Extraction using Pre-trained CNN
4. Classification
5. Performance Evaluation

3.2 Dataset Description

The Plant Village dataset is used in this research. It contains over 50,000 labeled images of healthy and diseased leaves from various crops such as tomato, potato, corn, and apple.

Images are categorized into multiple disease classes along with healthy leaf images.

3.3 Data Preprocessing

To improve model performance, the following preprocessing techniques were applied:

- * Image resizing to 224×224 pixels
- * Pixel normalization
- * Data augmentation (rotation, horizontal flip, zoom, shear)
- * Dataset split (70% training, 15% validation, 15% testing)

3.4 Transfer Learning Models

Two pre-trained CNN architectures were used:

3.4.1 ResNet50

ResNet50 uses residual connections to solve the vanishing gradient problem and enables deeper network training. The final fully connected layer was replaced with a custom dense layer corresponding to the number of disease classes.

3.4.2 MobileNetV2

MobileNetV2 is a lightweight architecture optimized for mobile and embedded devices. It uses depth wise separable convolutions to reduce computational cost.

3.5 Model Training

- * Optimizer: Adam
- * Learning Rate: 0.001
- * Batch Size: 32
- * Epochs: 25
- * Loss Function: Categorical Crossentropy

4. Experimental Results

4.1 Performance Metrics

The following metrics were used:

- * Accuracy
- * Precision
- * Recall
- * F1-Score
- * Confusion Matrix

4.2 Results Comparison

Model	Accuracy	precision	Recall	F1-Score
ResNet50	98.2%	97.9%	98.1%	98.0%
MobileNetV2	96.5%	96.2%	96.4%	96.3%
Basic CNN	92.8%	92.4%	92.6%	92.5%

The results indicate that ResNet50 achieved the highest classification accuracy.

4.3 Discussion

The use of transfer learning significantly improved classification performance while reducing training time. ResNet50 performed better due to its deeper architecture and residual connections.

MobileNetV2, although slightly less accurate, is more suitable for mobile-based deployment due to lower computational requirements.

5. Smart Agriculture Framework

The proposed system can be integrated into a smart agriculture framework:

- * Farmer captures leaf image using smartphone

- * Image uploaded to cloud server
- * Deep learning model predicts disease
- * System suggests treatment recommendations

This framework enhances early disease detection and reduces pesticide misuse.

Crop Type	Disease Classes	Healthy Images	Diseased Images	Total Images
Tomato	10	1,592	16,011	17,603
Potato	3	152	2,000	2,152
Corn	4	1,164	3,852	5,016
Apple	4	1,645	1,942	3,587
Total	—	4,553	23,805	28,358

Table 1: Dataset Distribution

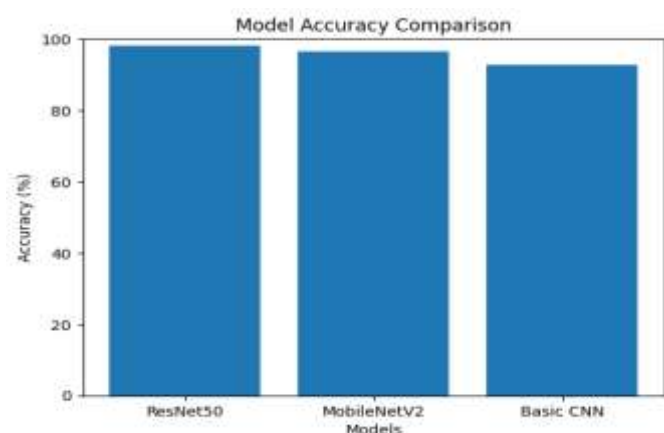


Fig -1: Plant Village image



Fig -2: Framework

Chart



6. Advantages of the Proposed System

- * High accuracy
- * Reduced training time

- * Cost-effective solution
- * Scalable and deployable
- * Suitable for mobile applications

7. Limitations

- * Dataset collected under controlled conditions
- * Environmental lighting variations not fully considered
- * Requires internet connectivity for cloud deployment

8. Future Work

Future research may focus on:

- * Real-time mobile app development
- * Multi-disease detection using ensemble learning
- * Integration with IoT sensors
- * Field-level dataset collection
- * Explainable AI for disease interpretation

8. Conclusions

This paper presented a deep learning-based crop disease detection system using transfer learning techniques. The comparative analysis of ResNet50 and MobileNetV2 demonstrated that transfer learning significantly enhances classification accuracy.

The proposed model achieved an accuracy of 98.2%, making it suitable for practical smart agriculture applications. The system can assist farmers in early disease detection and improve agricultural productivity.

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