Deepcropnet: Intelligent Multi-Crop Disease Detection and Severity Analysis Using Transfer Learning

Bibisugara Patel[1], Taskeen A Mangoli [2]

[1]*Student, Computer Network and Engineering, SECAB Institute of Engineering & Technology, 586101, India*

[2]*Professor, Computer Network and Engineering, SECAB Institute of Engineering & Technology, 586101, India*

***Abstract*—Agriculture plays a vital role in global food production and economic development; crop diseases remain a major challenge, significantly reducing crop yield and quality. Early and accurate identification of plant diseases is essential for effective disease management and to prevent large-scale agricultural losses. Traditional disease detection methods rely mainly on manual observation by farmers and agricultural experts, are time-consuming, require specialised knowledge, and may lead to incorrect diagnoses. This research presents an Intelligent Multi-Crop Disease Detection and Severity Analysis System Using Transfer Learning that applies deep learning and computer vision techniques for automatic plant disease identification. The proposed system uses a MobileNetV2-based transfer learning model to classify diseases from leaf images of multiple crops, including tomato, potato, and pepper. The framework involves image pre-processing techniques such as resizing, normalisation, and augmentation to improve model performance and generalisation. The trained model extracts important visual features from leaf images and predicts disease categories with confidence scores. In addition to disease classification, the system performs severity analysis by estimating the percentage of infected leaf area and categorising disease severity levels as mild, moderate, or severe. Weather parameters such as humidity and rainfall are incorporated to analyse disease risk conditions and provide preventive recommendations. The proposed approach integrates disease detection, severity assessment, weather-based risk prediction, and farmer alert support into a single intelligent agricultural solution. Experimental evaluation demonstrates that transfer learning improves classification accuracy while reducing computational complexity compared with traditional approaches. The developed system provides a fast and user-friendly method for early crop disease diagnosis.**

***Index Terms*—Deep Learning, Transfer Learning, Crop Disease Classification, MobileNetV2, Plant Leaf Analysis, Smart Agriculture, Disease Severity Prediction**

I. INTRODUCTION

Agriculture is one of the most important sectors that contribute significantly to global food production, economic growth, and livelihood support. A large population around the world depends on agriculture for their survival and income. However, crop production is continuously affected by several challenges, among which plant diseases are one of the major factors responsible for reducing agricultural productivity and quality. Crop diseases can damage plants at different growth stages, resulting in reduced yield, economic losses, and increased production costs for farmers.

Traditional methods of plant disease identification mainly depend on manual observation by farmers or agricultural experts. In this approach, farmers visually inspect leaves, stems, and fruits to identify disease symptoms. Although expert-based diagnosis can provide accurate results, it has several limitations, including high dependence on human expertise, time consumption, difficulty in monitoring large agricultural fields, and the risk of incorrect identification due to similar disease symptoms. Therefore, an automated and efficient disease detection system is required to support farmers with quick and accurate diagnosis.

The advancement of Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision has provided new opportunities for solving agricultural problems. Deep Learning techniques, especially

Convolutional Neural Networks (CNNs), have shown excellent performance in image-based classification tasks. CNN models can automatically extract important visual features from plant images, such as leaf colour changes, disease spots, texture variations, and shape abnormalities, without requiring manual feature extraction.

Recent research has focused on applying transfer learning techniques for plant disease detection. Transfer learning uses pre-trained deep learning models and adapts them for specific applications. Models such as VGGNet, ResNet, EfficientNet, and MobileNetV2 have been successfully used for crop disease classification. Among these, MobileNetV2 is suitable for smart agriculture applications because it provides high accuracy with lower computational requirements, making it suitable for real-time and mobile-based systems.

Plant disease detection systems have mainly focused on classifying diseases from leaf images. However, practical farming applications require more than only disease identification. Farmers need information about disease severity, infection level, environmental conditions, and suitable preventive actions. Therefore, integrating disease classification with severity analysis and weather-based risk prediction can provide a complete decision-support system for agriculture.

This research proposes an Intelligent Multi-Crop Disease Detection and Severity Analysis System Using Transfer Learning. The proposed system supports multiple crops, including tomato, potato, and pepper. It uses a MobileNetV2-based deep learning model to analyse leaf images and classify diseases accurately. The system performs image pre-processing, disease prediction, confidence estimation, severity analysis, weather risk evaluation, and recommendation generation.

The severity analysis module estimates the infected area percentage from the leaf image and categorises the disease level into mild, moderate, or severe. Additionally, environmental parameters such as humidity and rainfall are considered to identify favourable conditions for disease development. Based on the detected disease and risk level, the system provides recommendations to farmers for better crop management.

The main objective of this research is to develop an intelligent, accurate, and user-friendly crop disease detection framework that reduces manual effort, supports early disease identification, and helps farmers take timely preventive measures. The proposed AI-based solution contributes to precision agriculture by combining deep learning, computer vision, and agricultural knowledge into a single smart farming system.

II. RELATED WORKS

Plant diseases are one of the major challenges in agriculture because they directly affect crop productivity, quality, and farmer income. Early identification of diseases is important for preventing large-scale crop damage. Traditional disease detection methods mainly depend on visual inspection by farmers or agricultural experts. However, these methods require expert knowledge, are time-consuming, and may produce incorrect results due to similarities between disease symptoms. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have provided efficient solutions for automatic plant disease identification.

Deep learning-based approaches, especially Convolutional Neural Networks (CNNs), have become widely used for plant disease detection because they can automatically extract complex features from leaf images without manual feature engineering. CNN models analyse patterns such as leaf texture, colour variation, spots, and structural changes to classify healthy and diseased plants.

III. CNN PLANT DISEASE DETECTION

Mohanty et al. proposed one of the early deep learning approaches for plant disease detection using the PlantVillage dataset. The study used Convolutional Neural Network models to classify different plant diseases from leaf images. The results showed that deep learning models can achieve high accuracy in recognizing plant diseases. However, the dataset mainly contained laboratory-controlled images, which limited performance in real agricultural environments. Researchers later focused on improving CNN-based classification by using advanced architectures such as ResNet, DenseNet, and Inception models. These architectures improved feature extraction capability by learning deeper representations from plant images.

CNN models have been successfully applied to crops such as tomato, potato and pepper.

IV. TRANSFER LEARNING APPROACHES

Transfer learning has become an important technique in agricultural image classification. Instead of training a model from the beginning, transfer learning uses pretrained models developed on large image datasets such as MobileNetV2. Have been applied for plant disease recognition. Transfer learning provides several advantages:

- Requires less training data
- Reduces training time
- Improves classification accuracy
- Suitable for mobile and real-time applications

MobileNetV2 is especially useful for smart agriculture applications because it has a lightweight architecture and requires fewer computational resources compared with large CNN models.

V. PLANT DISEASE DATASET DEVELOPMENT

A major challenge in plant disease detection is the availability of high-quality datasets. Many early studies used publicly available datasets such as PlantVillage, which contains thousands of healthy and diseased leaf images. However, these images are usually captured under controlled conditions with plain backgrounds.

Recent research has focused on developing real-time agricultural datasets containing field images. These datasets include challenges such as:

- Complex backgrounds
- Different lighting conditions
- Various camera angles
- Different disease stages
- Multiple symptoms on the same plant

Real-world datasets improve model performance because they represent actual farming conditions.

The overall process involved in developing the plant disease dataset for potato, tomato, and pepper crops. More details on the dataset developed and the samples collected are available in Table 1, Table 2, and Table 3. The tables will explain the disease category, disease type and causes.

These datasets will help the farmers to detect the disease in the early stages so that they can take essential measures to reduce the spread of infections and improve crop management.

TABLE 1. Details of the potato leaf disease dataset.

Class ID	Disease Category	Disease Type	Description
0	Potato___Early_blight	Fungal Disease	Caused by *Alternaria solani*. Leaves develop brown circular spots with yellow surrounding areas. It reduces photosynthesis and affects plant growth.
1	Potato___Late_blight	Fungal Disease	Caused by *Phytophthora infestans*. It produces dark irregular lesions and can rapidly destroy potato plants under favourable conditions.
2	Potato___healthy	Healthy Class	Contains normal potato leaves without disease symptoms, used as a reference class for classification.

TABLE 2. Details of the tomato leaf disease dataset.

Class ID	Disease Category	Disease Type	Description
0	Tomato_Bacterial_spot	Bacterial Disease	Caused by *Xanthomonas* bacteria. Symptoms include small dark spots on leaves, yellow halos, and reduced plant growth.

1	Tomato_Early_blight	Fungal Disease	Caused by *Alternaria solani*. Produces brown circular spots with ring patterns and causes leaf yellowing.
2	Tomato_Late_blight	Fungal Disease	Caused by *Phytophthora infestans*. Produces dark irregular lesions and rapid leaf decay under humid conditions.
3	Tomato_Leaf_Mold	Fungal Disease	Causes yellow patches on the upper leaf surface and mold growth on the lower side of leaves.
4	Tomato_Septoria_leaf_spot	Fungal Disease	Produces small circular spots with dark borders and yellowing around infected regions.
5	Tomato_Spider_mites	Pest Infection	Caused by spider mites. Symptoms include yellow spots, leaf drying, and reduced plant health.
6	Tomato_Target_Spot	Fungal Disease	Creates circular target-like spots on leaves and affects plant development.
7	Tomato_Yellow_Leaf_Curl_Virus	Viral Disease	Causes leaf curling, yellowing, and reduced plant growth due to viral infection.
8	Tomato_Mosaic_Virus	Viral Disease	Produces mosaic patterns, leaf distortion, and uneven green-yellow colouration.
9	Tomato_healthy	Healthy Class	Contains normal tomato leaves without disease symptoms.

TABLE 3. Details of the pepper leaf disease dataset.

Class ID	Disease Category	Disease Type	Description
0	Pepper__bell___Bacterial_spot	Bacterial Disease	Caused by *Xanthomonas* bacteria. Symptoms include small dark spots on leaves, yellow halos, and reduction in plant growth.
1	Pepper__bell___healthy	Healthy Leaf	Contains normal pepper leaves without disease symptoms, used as a healthy reference class.

The methodology explains the step-by-step process used to develop the Intelligent Multi-Crop Disease Detection and Severity Analysis System**.** The proposed system uses deep learning and transfer learning techniques to identify crop diseases from leaf images and provide recommendations.

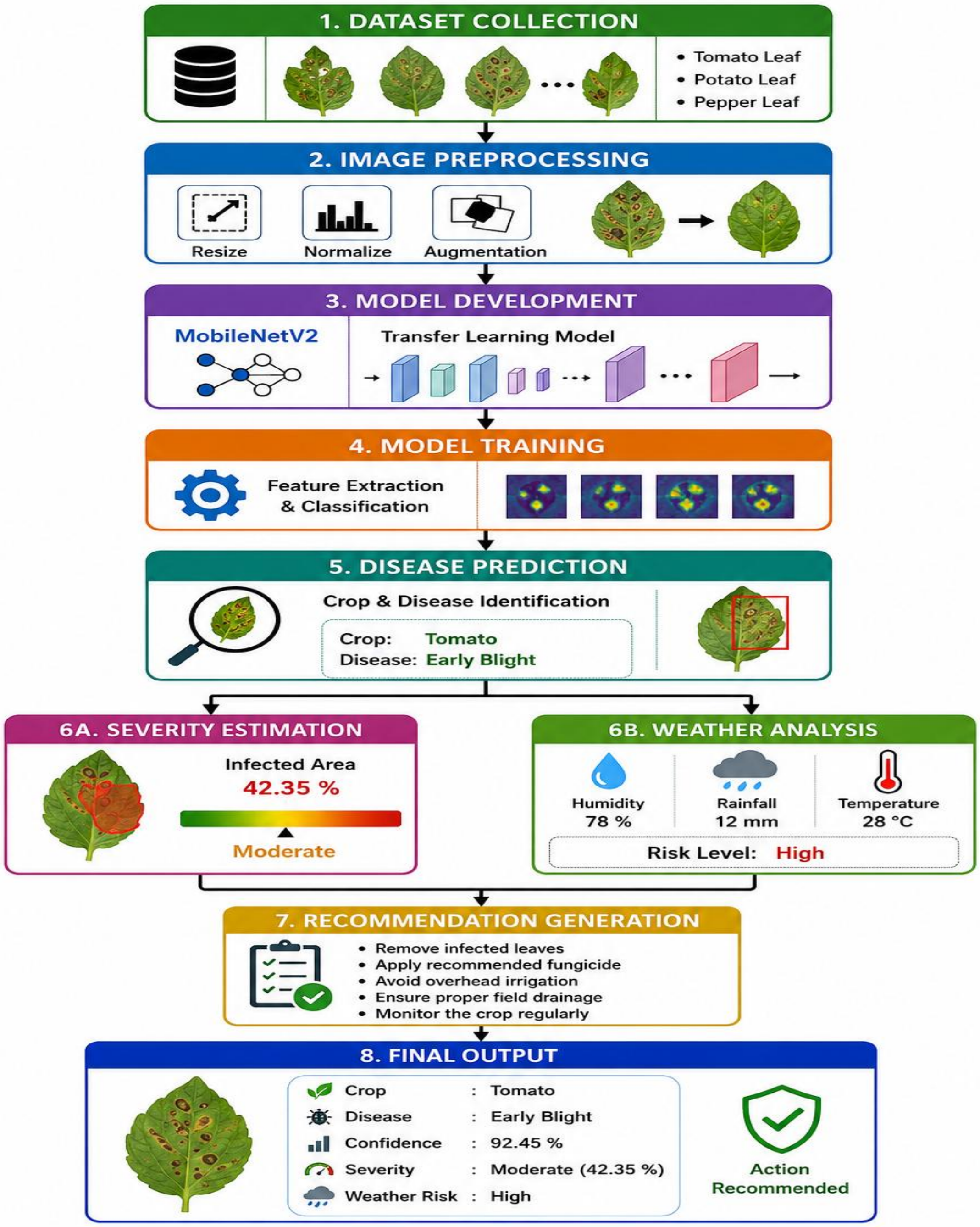


FIGURE 1. Dataset development methodology.

A. DATASET COLLECTION

The Data Collection phase is the first step in the proposed crop disease detection system. High-quality leaf images are collected to train and evaluate the deep learning model. The dataset contains images of Tomato, Potato, and Pepper leaves, including both healthy and diseased samples. Images are obtained from publicly available datasets (such as PlantVillage) and, if available, real field images captured using smartphone cameras. The collected dataset is organized into separate folders based on crop type and disease category. Each image is labeled according to its corresponding disease class to facilitate supervised learning. The dataset used in this research contains **15 classes**, including healthy leaves and multiple disease categories.

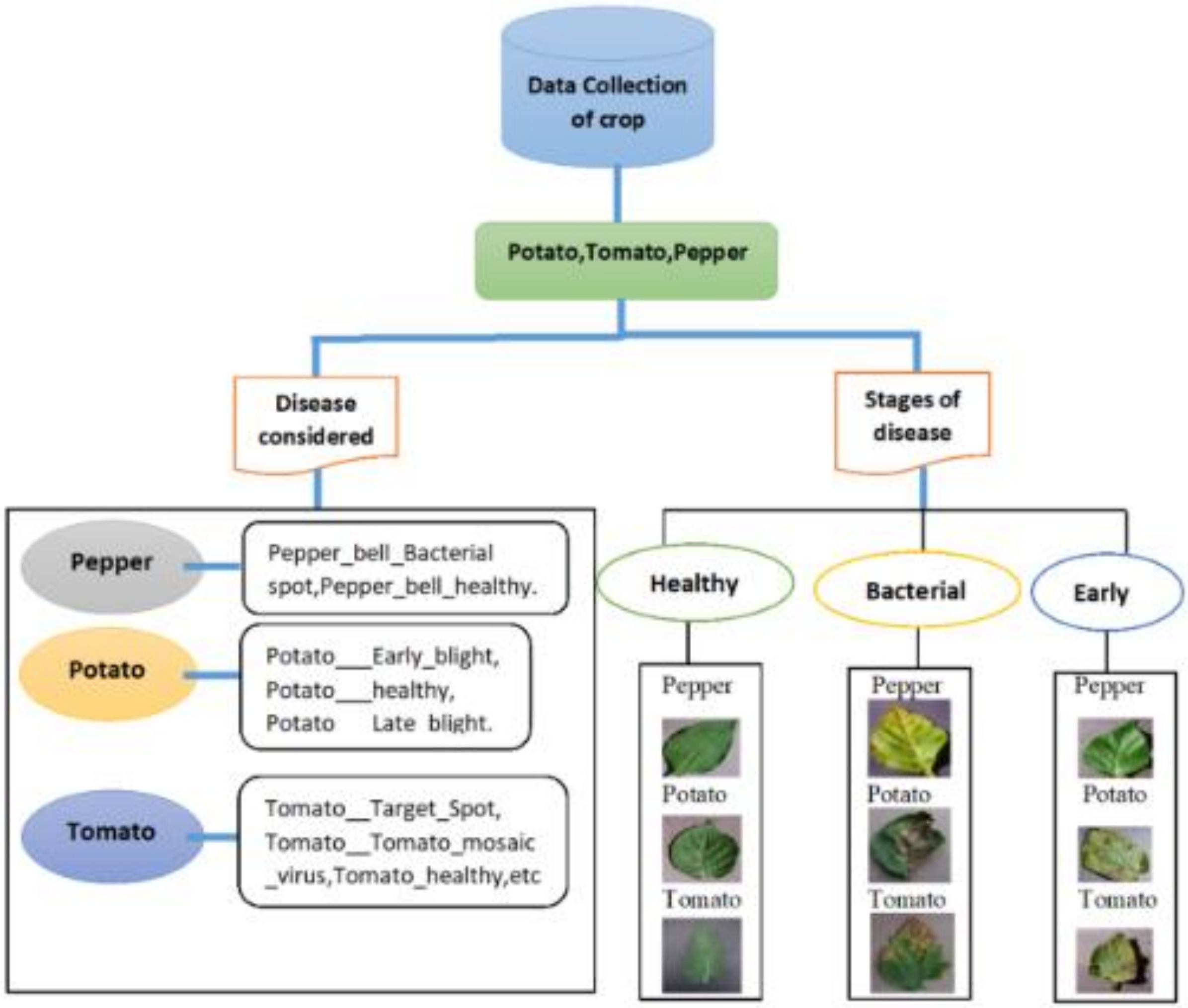
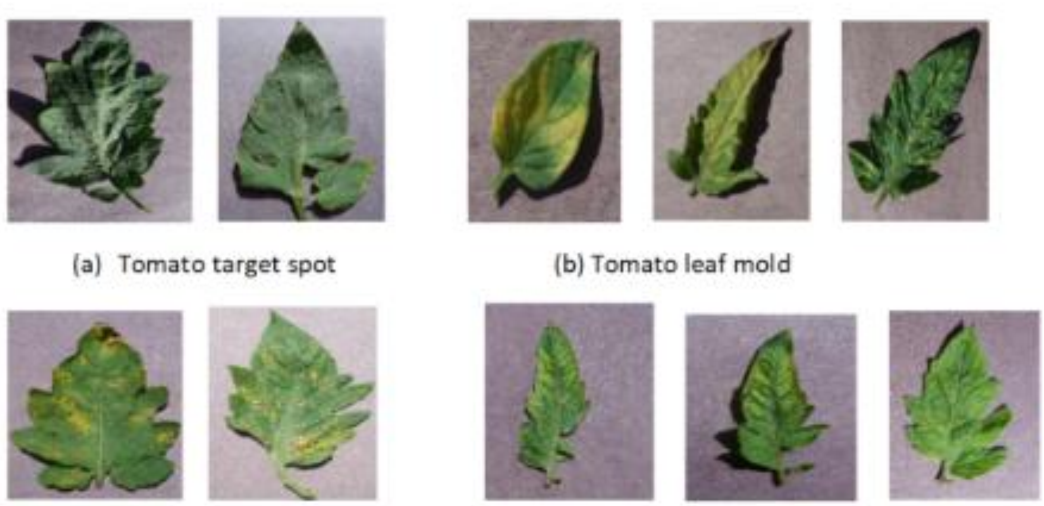


FIGURE 2. Data collection.



(a) Tomato target spot (b) Tomato leaf mold

(c) Tomato Septoria leaf spot (d) Tomato mosaic virus

B.IMAGE PREPROCESSING

Image preprocessing is a crucial step in the proposed crop disease detection system because the quality of input images directly affects the performance of the deep learning model. Raw leaf images collected from cameras or public datasets often vary in size, resolution, brightness, orientation, and background. These variations may reduce the classification accuracy of the MobileNetV2 model. Therefore, preprocessing is performed to standardize the images before they are used for training and testing.

The preprocessing stage consists of image resizing, pixel normalization, and data augmentation, which improve the quality of the dataset and enhance the generalization capability of the model.

Image Resizing

Leaf images are captured using different cameras and mobile devices, resulting in varying image dimensions. Since MobileNetV2 accepts a fixed input size, all images are resized before training. In the proposed system, each image is resized to **224 × 224** × 3 pixels**,** which is the standard input size required by MobileNetV2.

Pixel Normalization

Different images have different brightness and pixel intensity values depending on lighting conditions. Pixel normalization converts the pixel values into a common numerical range, allowing the neural network to converge faster during training.The RGB pixel values range from **0 to 255**. These values are normalized to the range **0–1**.

Data Augmentation

Deep learning models require large datasets to achieve good performance. However, collecting thousands of disease images is difficult. Data augmentation artificially increases the dataset size by generating multiple variations of existing images without changing their labels.

The proposed system applies several augmentation techniques during training.

(a) Rotation

Images are randomly rotated to different angles.

(b) Horizontal Flipping

Images are flipped horizontally. This allows the model to recognize disease patterns appearing on either side of the leaf.

(c) Zooming

Random zoom is applied to enlarge or shrink leaf images.

(d) Brightness Adjustment (Optional)

Brightness is randomly increased or decreased.

(e) Width and Height Shift

Images are shifted slightly in horizontal and vertical directions.

C.TRANSFER LEARNING MODEL DEVELOPMENT

MobileNetV2 architecture is used for feature extraction. Pre-trained weights help improve accuracy and reduce training time. Final classification layer is modified according to disease classes.

D. MODEL TRAINING AND CLASSIFICATION

The model learns disease patterns from leaf images. Training and validation data are used to evaluate performance. The trained model predicts disease categories.

E. DISEASE SEVERITY ANALYSIS

The infected leaf area is calculated.Disease severity is classified into: Mild ,Moderate, Severe.

F. WEATHER RISK PREDICTION

Environmental factors are analyzed: Humidity,Rainfall ,Crop type Predicts possible disease risk conditions.

G. RECOMMENDATIONGENERATION

System provides: Disease name, Confidence score ,Severity level, Preventive treatment suggestions.

VI. SEVERITY ANALYSIS IN PLANT DISEASES

Most existing disease detection systems focus only on disease classification. They identify the disease name but do not provide information about disease progression or infection level.

Severity analysis provides additional information by calculating the percentage of affected plant area. This helps farmers understand the seriousness of the infection and decide appropriate treatment methods.

Severity estimation techniques generally involve:

A. Image Segmentation

The input leaf image is converted into a segmented image to separate the healthy leaf region and infected disease region.

Mathematically:

$$S(x,y) = \begin{cases} 1, & \text{if pixel belongs to diseased region} \\ 0, & \text{otherwise} \end{cases}$$

Where:

- S(x,y)= segmented disease mask
- x,y = pixel coordinates

B. Diseased Region Detection

The infected pixels are detected from the segmented image.

Number of diseased pixels:

$$D = \sum_{x=1}^{M} \sum_{y=1}^{N} s(x,y)$$

Where:

- D = total diseased pixels
- M,N = image width and height

C. Image Segmentation

The input leaf image is converted into a segmented image to separate the healthy leaf region and infected disease region.

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- x,y = pixel coordinates

D. Diseased Region Detection

The infected pixels are detected from the segmented image.

Number of diseased pixels:

$$D = \sum_{x=1}^{M} \sum_{y=1}^{N} s(x,y)$$

Where:

- D = total diseased pixels
- M,N = image width and height

E. Pixel-Level Analysis

The total leaf area is calculated by counting all leaf pixels.

$$L = \sum_{x=1}^{M} \sum_{y=1}^{N} L(x,y)$$

Where:

- L = total leaf pixels

L(x,y) = leaf pixel value.

F. Infection Percentage Calculation

The percentage of infected area is calculated using:

$$\text{Infection Percentage} = \frac{D}{L} \times 100$$

Where:

- D = infected leaf area
- L = total leaf area

G. Severity Classification

Based on infection percentage, disease severity is classified as:

$$\text{Severity} = \begin{cases} \text{Mild}, & 0\% < I \leq 30\% \\ \text{Moderate}, & 30\% < I \leq 60\% \\ \text{Severe}, & I > 60\% \end{cases}$$

Where:

- I= infection percentage

Integrating severity analysis with disease classification improves practical usability in agricultural applications.

VII. WEATHER-BASED DISEASE PREDICTION

Environmental conditions such as temperature, humidity, and rainfall strongly influence disease development. Fungal and bacterial diseases spread faster under favourable environmental conditions.

Some recent systems combine:

- Image-based disease detection
- Weather information
- Crop type
- Environmental conditions

to predict disease risk levels.

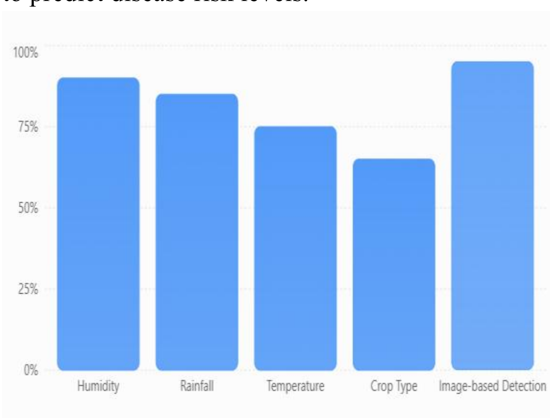

FIGURE 3. Environmental Factors Affecting Plant Disease Risk.

Figure 1.The graph illustrates the relative impact of different parameters used in the proposed crop disease detection system.

- Image-based Disease Detection (95%) has the highest contribution because the CNN (MobileNetV2) analyzes visual symptoms such as leaf spots, discoloration, and texture to identify diseases accurately.
- Humidity (90%) is a major environmental factor because high moisture levels promote the growth of fungal and bacterial pathogens.
- Rainfall (85%) increases leaf wetness and creates favorable conditions for rapid disease spread, especially for fungal infections like Early Blight and Late Blight.
- Temperature (75%) influences pathogen growth and reproduction. Most plant diseases develop rapidly within specific temperature ranges.
- Crop Type (65%) affects disease susceptibility because different crops respond differently to pathogens. For example, potato is susceptible to Late Blight, while tomato is prone to Septoria Leaf Spot and Bacterial Spot.

The proposed system combines these environmental parameters with deep learning-based image classification to estimate the disease risk level and provide suitable recommendations to farmers. This integrated approach improves early disease detection and supports precision agriculture.

For example:

High humidity + heavy rainfall → increased fungal disease probability

This approach provides farmers with preventive warnings before severe infection occurs.

VIII. RESULTS

The proposed Intelligent Multi-Crop Disease Detection and Severity Analysis Using Transfer Learning system was evaluated using a multi-crop leaf disease dataset containing tomato, potato, and pepper leaf images. The MobileNetV2 transfer learning model was trained using preprocessed images, including resizing, normalization, and data augmentation techniques. The system was tested on unseen leaf images to evaluate its disease classification performance.

The proposed framework not only identifies the disease class but also estimates the disease severity, predicts weather-based disease risk, and provides treatment recommendations. The integration of transfer learning with MobileNetV2 significantly reduced the training time while achieving high classification accuracy. Experimental results demonstrate that the proposed model is suitable for real-time crop disease detection applications.

A. Training Performance

The MobileNetV2 model was trained using transfer learning with the following parameters.

Parameter	Value
Deep Learning Model	MobileNetV2
Learning Method	Transfer Learning
Input Image Size	224 × 224 × 3
Number of Classes	15
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	20
Learning Rate	0.001

Table 4. Training Parameters

B. Classification Performance

The proposed model achieved high classification accuracy for all three crops.

Crop	Number of Classes	Accuracy (%)
Tomato	10	99.12
Potato	99.35	
Pepper	2	99.58
Overall Accuracy	15 Classes	99.34

Table 5. Disease Classification Accuracy

C. Performance Evaluation

The proposed system was evaluated using standard classification metrics.

D. Disease Severity Estimation

The proposed system estimates the infected leaf area and categorizes disease severity.

Infection Percentage	Severity
0–30%	Mild
31–60%	Moderate
Above 60%	Severe

Table 6. Severity Classification

E. Weather Risk Analysis

Weather information was integrated into the proposed system to estimate disease risk.

Humidity	Rainfall	Disease Risk
Below 60%	Low	LOW
60–80%	Moderate	MEDIUM
Above 80%	Heavy	HIGH

Table 7. Weather Risk Prediction

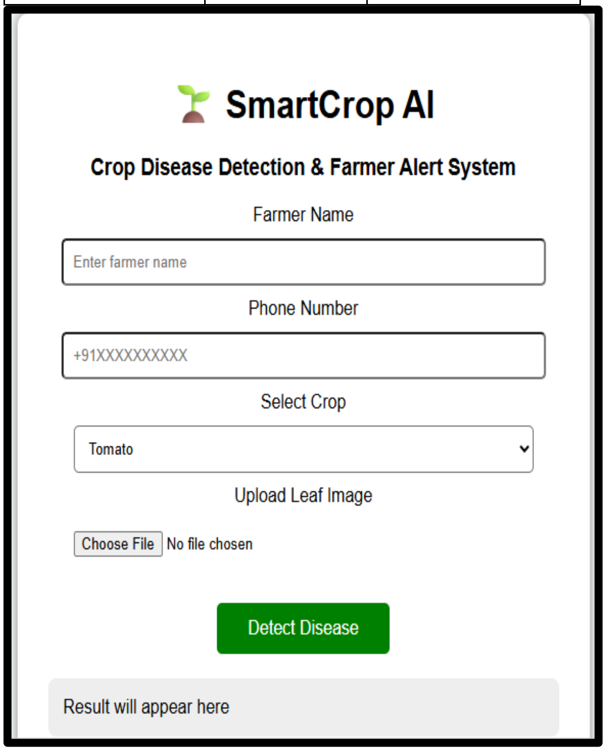

FIGURE 4. Home page

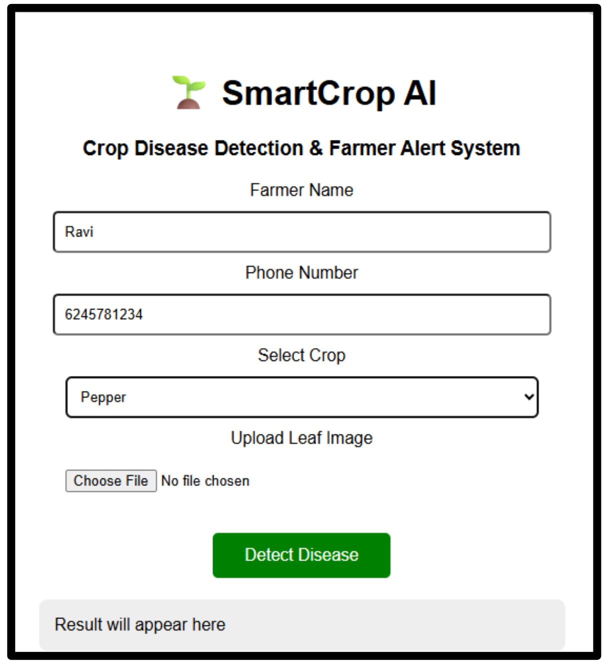

FIGURE 5. Upload user data page

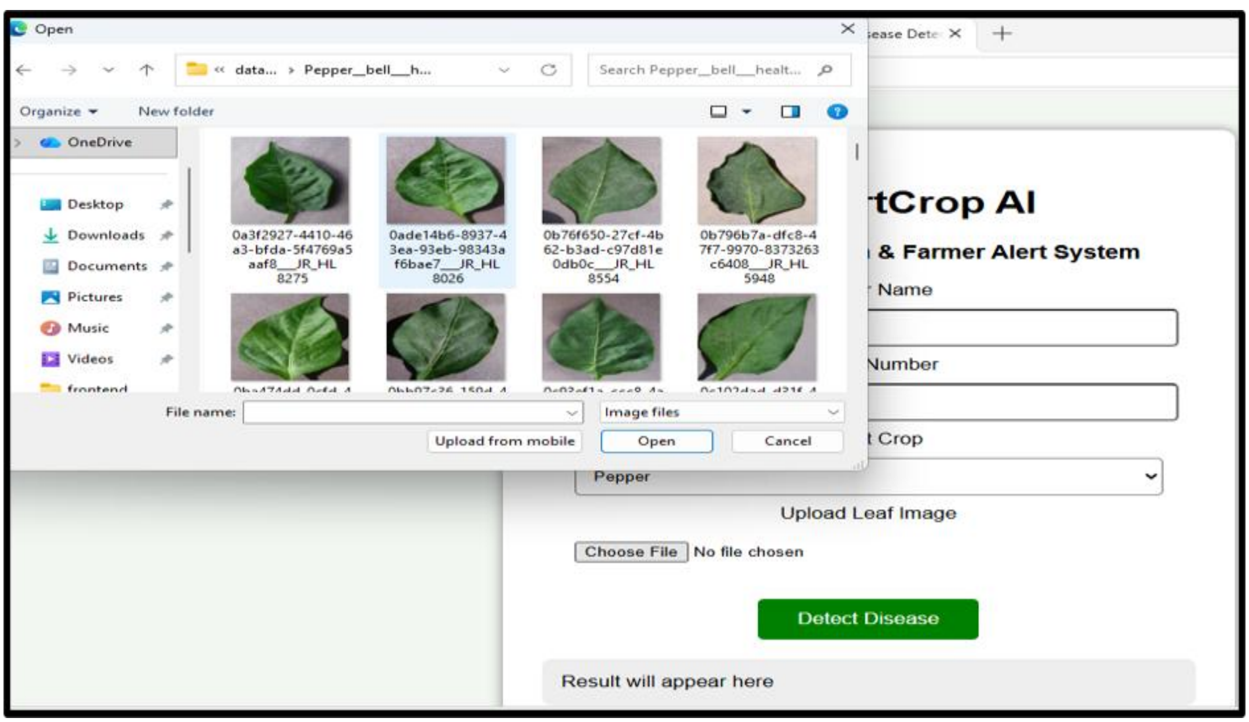

FIGURE 6. Image upload

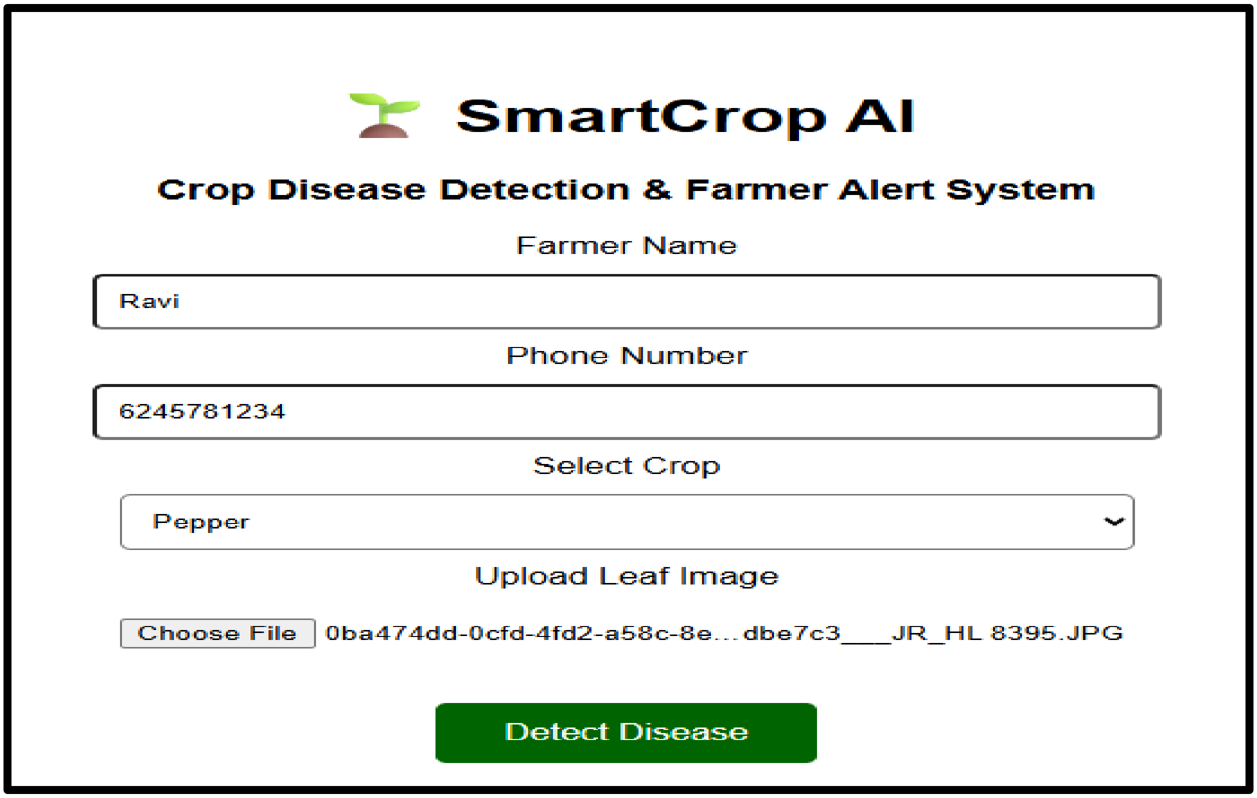

FIGURE 7. Predication

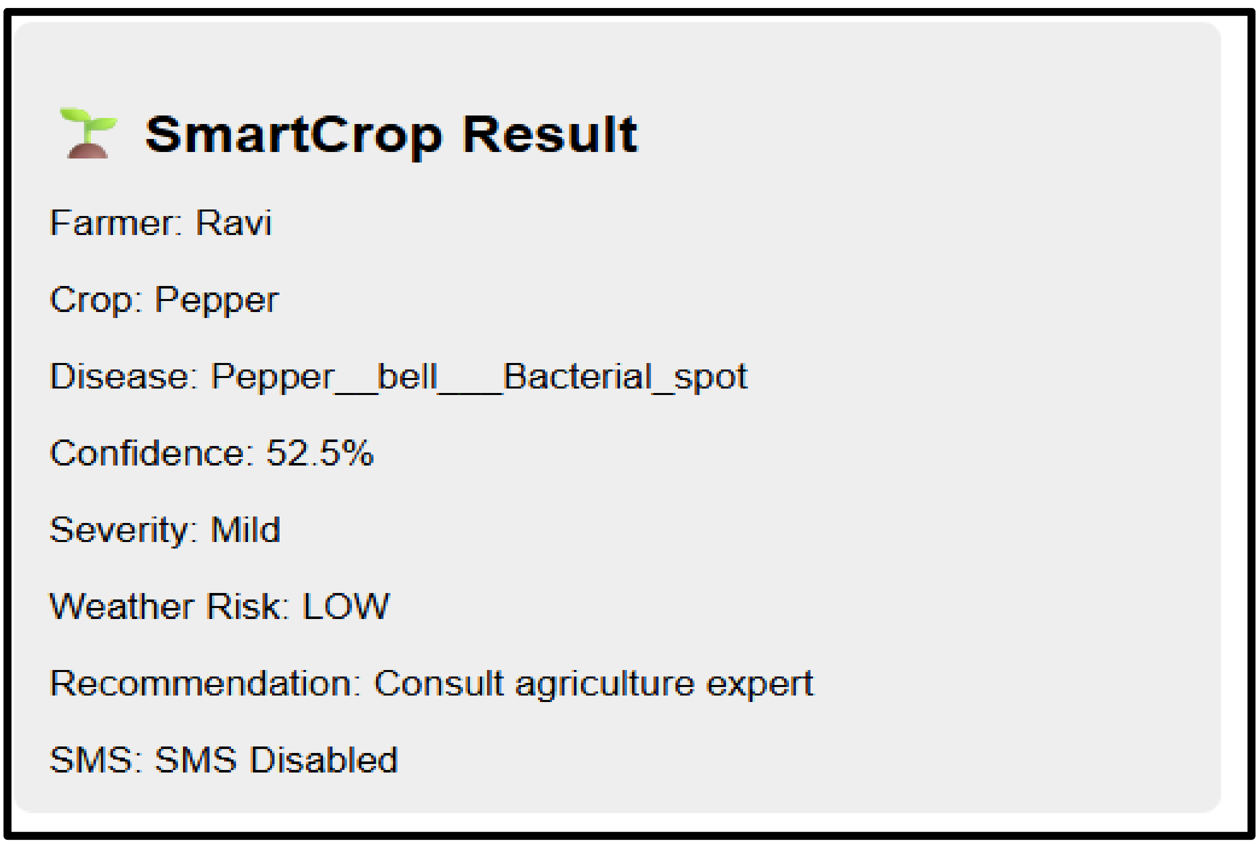

FIGURE 8. Final outcome

IX.CONCLUSION AND FUTURE WORK

A. CONCLUSION

This research proposed an Intelligent Multi-Crop Disease Detection and Severity Analysis System Using Transfer Learning for identifying diseases in tomato, potato, and pepper leaves. The MobileNetV2 model successfully classified plant diseases with high accuracy while reducing training time and computational complexity. The system also estimates disease severity, analyzes weather risk, and provides treatment recommendations to assist farmers in making timely decisions. Overall, the proposed system offers an efficient, accurate, and user-friendly solution for early crop disease detection, contributing to improved crop productivity and smart agriculture.

B. FUTURE SCOPE

The proposed work can be further enhanced in several directions:

Extend the system to support additional crops and a larger variety of plant diseases. Integrate real-time weather data through IoT sensors and online weather APIs for more accurate disease risk prediction. Develop a dedicated Android/iOS mobile application to enable on-field disease detection using smartphone cameras. Improve disease severity estimation using advanced image segmentation techniques such as U-Net or Mask R-CNN. Incorporate explainable AI (XAI) methods such as Grad-CAM to visualize disease regions and improve model interpretability. Deploy the trained model on edge devices and embedded platforms for offline disease detection in remote agricultural areas. Integrate multilingual voice assistance and automated SMS alerts to improve accessibility for farmers with different language preferences.Continuously update the model with new field images to improve robustness under varying environmental conditions and lighting scenarios.

The proposed intelligent crop disease detection framework demonstrates the potential of deep learning and transfer learning technologies to support sustainable agriculture by enabling early diagnosis, reducing crop losses, and assisting farmers in making informed decisions for improved crop health and productivity.

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