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Early Multi-Class Disease Detection in Chili Plant Leaves Using Convolutional Neural Networks: A Comparative Study

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Abstract

Chili is an important economic and nutritional crop with a relatively limited availability of different disease-resistant varieties. Leaf diseases, including those caused by fungi, bacteria, viruses, pests, or nutritional deficiencies, significantly compromise production and crop quality. Early detection of these diseases is key to reducing yield loss; however, traditional visual examinations are limited by time constraints, human subjectivity, and low detection sensitivity at early stages of infection. To overcome these challenges, this study proposes a deep learning–based framework for early multi-class detection of chili leaf diseases using convolutional neural networks (CNNs). A real-field dataset comprising 16,392 high-resolution images of chili leaves across six disease and healthy classes was collected from multiple regions of Bangladesh. The dataset was preprocessed, augmented, and split into training and validation sets using an 80:20 ratio. Five pre-trained CNN architectures—DenseNet121, EfficientNetB3, MobileNetV2, ResNet50, and InceptionV3 were evaluated using a transfer learning strategy. Experimental results demonstrate that MobileNetV2 achieved the best performance, attaining an overall classification accuracy of 96%. The results indicate that the proposed system demonstrates strong generalization capability and effectively discriminates visually similar chili leaf diseases. This work can be considered a valuable application in precision agriculture, providing an efficient, automated, and practical approach for in situ early diagnosis of chili leaf diseases through smart farm management.

1. Introduction

Chilli is a commercially significant and nutritionally valuable crop grown globally. Chilli, however, is under great threat due to several foliar diseases inflicted by fungi, bacteria, pests, and physiological deficiencies. These diseases cause considerable reductions in yield and quality of the crop if not identified and managed early. Chilli Leaf Pests & Disease Problems Several common chilli plant leaf problems include algal leaf spot, anthracnose, black spot, bacterial leaf spot, chilli mite infestation, chilli leaf minor damage, chilli pest attack, curl leaf, greening, chilli sooty mold, caterpillar larval herbivory (deficiency), and yellow spot, which can further be consulted at Healthy Chilli Leaves. These diseases share many visual symptoms that are very difficult to manually distinguish in early stages, and the accuracy of such a discrimination is quite low. Conventional disease assessment is conducted through visual inspections by farmers or experts; however, these processes are slow, subjective, and ineffective during the early stages of infection. To address these constraints, automated image-based disease detection with deep learning has achieved much focus in the field of precision agriculture. This paper presents a CNN architecture for early multi-class classification of chilli leaf diseases. Thirteen classes of leaf conditions are grouped by high-resolution images and comparative analysis using five pre-trained deep learning models: DenseNet121, EfficientNetB3, MobileNet, ResNet50, and InceptionV3. The potential exists to take diagnostic decisions more accurately and faster and towards more sustainable and efficient chilli crop management strategies.

1.1 **Background**

Recent advancements in deep learning have significantly enhanced detection systems. Moreover, a multitude of convolutional neural network (CNN) architectures have been investigated in recent years, demonstrating considerable accuracy in classifying leaf images and identifying plant diseases. The application of these methodologies facilitates the automation of disease detection and diagnosis in the early stages, thereby enabling farmers to implement preventative strategies and mitigate crop losses. Therefore, combining these methods with image processing and deep learning is becoming a prominent research area in smart agriculture and precision farming (Barbedo, 2018).

Meanwhile, deep learning approaches have been utilized to detect plant diseases through monitoring leaf visual symptoms. In particular, CNN-based models have demonstrated strong performance in feature extraction and classification. The research, which involved extensive testing on tomato leaves affected by political damage, showed that Convolutional Neural Network (CNN) methods can automatically learn to identify important features from images. This allows for the classification of different types of political damage without needing to manually define these features (Brahimi et al., 2017).

A further important investigation highlighted the efficacy of a deep learning model in diagnosing plant diseases, leveraging extensive image datasets. The research assessed the performance of several convolutional neural network (CNN) architectures in the identification of plant diseases. The findings indicated that deep learning models attained elevated classification accuracy, surpassing the performance of traditional machine learning techniques in the context of agricultural disease identification (Ferentinos, 2018).

Large-scale plant disease image datasets also facilitate research development in this field. In an effort to facilitate the creation of automated systems for disease recognition, an open-access image database of plant leaves, including healthy and diseased samples, was established. Researchers have widely used the dataset for training and evaluating machine learning and deep learning models for classifying plant diseases (Hughes & Salathé, 2015).

Agricultural applications of deep learning are becoming more common, as they can analyse large amounts of visual data. A recent survey highlighted applications of deep learning techniques in crop monitoring, yield prediction, and plant disease detection. According to (Kamilaris & Prenafeta-Boldú, 2018) one of the main applications of deep learning is image analysis, particularly convolutional neural networks, which are well known for their high performance in disease recognition from leaf images, thereby improving decision-support systems in agriculture.

In the last few years, deep learning-based plant disease detection in images has yielded considerable performance. A research paper showed that convolutional neural networks (CNNs) trained on plant leaf datasets can accurately classify many diseases. Suggested solution. Similar to the two contributions described above, a group of researchers presented a deep learning approach for an automated image analysis system that can help farmers and agricultural engineers diagnose plant diseases (Mohanty et al., 2016).

Researchers have investigated the use of deep convolutional neural networks (DCNNs) for classifying leaf-cut images collected with mobile devices to help recognize diseases under real-world conditions. This work showed that CNN-based models can accurately detect and classify plant diseases from images collected in uncontrolled environments, which lends itself well to practical agricultural applications (Picon et al., 2019).

Machine learning, a domain dedicated to data processing and analysis, has proven valuable in the identification of diseases affecting cassava leaves through deep learning methodologies. Research conducted by Ramcharan et al. The 2017 study underscored the effectiveness of a supervised Convolutional Neural Network (CNN) model in differentiating between images of diseased and healthy leaves. After being trained on a large dataset of both diseased and healthy leaf samples, the model showed a high level of accuracy in its classifications. Consequently, this finding illustrates the potential application of artificial intelligence in the surveillance of crop diseases. A method was developed that used deep neural networks to classify diseases based on images of leaves. Results show that CNN models can indeed automatically learn latent visual features of plant disease symptoms and achieve reliable classification performance. The growing recognition of this method further validated the use of deep learning algorithms in systems designed to automatically detect plant diseases (Sladojevic et al. 2016).

1.2 Aim

This paper attempts to construct an efficient and precise deep learning-based system for the early detection and multi-class classification of chilli leaf diseases using high-resolution chilli leaf photos. To this end, a large dataset is built that contains samples of chilli leaf disease and healthy leaves, aiming to test and compare the performance of different pre-trained CNN models and to select an appropriate model for accurate disease diagnosis. Furthermore, this research aims to improve model robustness through proper image preprocessing and data augmentation methods that enhance generalization in a real-world, discriminating environment. This framework seeks to improve rapid disease detection in the field, help farmers make informed decisions and increase knowledge of better crop management and sustainable chilli production.

2. Dataset Description

The dataset used in this study includes images of chili plant leaves, representing both healthy and diseased conditions. The collected images were then categorized into six different groups, based on the specific symptoms of the diseases seen on the leaves. These classifications are Bacterial Spot, Cercospora Leaf Spot, Curl Virus, Healthy Leaf, Nutrition Deficiency, and Powdery Mildew. Each dataset contains many images, which helps to effectively train and evaluate the deep learning models. The dataset comprises 16,392 images, each showing different visual characteristics of chili leaf conditions. Specifically, the Bacterial Spot class includes 2,732 images, while the Cercospora Leaf Spot class contains 1,518 images. Furthermore, the Curl Virus is represented by 1,272 images, and 1,318 images

are classified as Healthy Leaf. The Nutrition Deficiency category includes 966 images, and Powdery Mildew is represented by 674 images. This dataset's heterogeneity facilitates the model's ability to discern unique patterns and characteristics linked to both diseased and healthy leaves. To enhance the model's robustness and its capacity to generalize, image preprocessing and augmentation methods were employed on the dataset. These methods serve to augment the diversity of the training data, thereby mitigating the likelihood of overfitting throughout the model training process. Sample images from each class within the chili leaf dataset utilized in this investigation are presented in Fig. 1.

Table 1
Description of Classes in the Chili Leaf Dataset

S.No	Class Name	Total Images	Description
1	Bacterial Spot	2732	A bacterial disease characterized by small dark spots on the leaf surface, often surrounded by yellow halos that gradually damage the leaf tissue.
2	Cercospora Leaf Spot	2732	A fungal disease that appears as circular or irregular brown spots on the leaves, which may expand and reduce the plant’s photosynthetic ability.
3	Curl Virus	2732	A viral infection that causes curling, distortion, and discoloration of leaves, leading to stunted plant growth and reduced crop yield.
4	Healthy Leaf	2732	Leaves that show normal green color and structure without any visible symptoms of disease or nutrient deficiency.
5	Nutrition Deficiency	2732	Leaves affected by insufficient nutrients, often showing yellowing, discoloration, or abnormal patterns due to lack of essential minerals.
6	Powdery Mildew	2732	A fungal disease identified by white powder-like patches on the leaf surface, which can weaken the plant and reduce productivity.

3. Methodology

Technique includes collecting the data, preprocessing data, enlarging it, and classification of chilli leaf diseases employing five states of the art deep learning models.

2.1. Data Collection

The dataset used in this work is a set of chilli leaf images with high resolution that are captured from the chilli cultivation fields in different regions in Bangladesh, such as (Ashulia, Narsingdi, Cumilla, Feni, Noakhali, and Laksham). Image acquisition was performed from March 2025 to May 2025 in the field under natural environmental conditions.

All photographs were taken with a smartphone camera under natural daylight and near the chilli plants. The dataset consists of healthy and diseased chilli leaf images, including the following six classes such as Bacterial Sport, Cercospora Leaf Sport, Curl Virus, Nutrition Deficiency, Powdery Mildew, and Healthy leaves. In order to guarantee robustness, images were captured with changed lighting conditions and surroundings, which are consistent with the field agricultural environments.

The raw images were resized into 1000×1000 pixels after collection, subsequently normalized to the same illumination conditions, and pre-processed to remove duplicate or quality-degraded samples. The dataset was then split into 80% training, and 20% validation sets to enable good model learning and performance evaluation.

To do the disease classification, we used 5 pre-trained CNN models (DenseNet121, EfficientNetB3, MobileNet, ResNet50, and InceptionV3). We used accuracy, precision, recall, and F1-score to evaluate the performance of the model, which showed that deep learning can be an effective tool in chilli leaf disease detection under realistic field conditions.

2.2. Materials (Camera Specifications)

Chilli leaf photographs were recorded under field conditions using an HONOR 90 and a Redmi K20 smartphone. The 200 MP primary camera of the HONOR 90 captured high-resolution images of subtle leaf texture, discoloration, and early stages of disease. At the same time, the Redmi K20's 48 MP one produced consistent-quality macro images for close-up details like lesions and pest damage. Both phones worked well under varying illumination conditions, and their autofocus features increased the diversity of the dataset collected from different types of smartphones, diminishing device-dependent bias.

2.3. Image Pre-processing and Classification

The acquired chilli leaf images were initially categorized into their respective disease and healthy classes. The names of the images were stored according to their class labels before we trained on the model, and all the images were resized to 1000 × 1000. Such systematic organization guaranteed the data consistency, diversity, and relevance for real-world chilli leaf disease detection. The adopted preprocessing strategy aimed to simulate practical farming processes and constructed a robust image generation model that can guarantee unseen data classification with high confidence. The complete processing pipeline, from raw image acquisition to the final data for deep learning model training, is presented in Fig. 2.

The image preprocessing and classification pipeline consists of the following steps:

- • **Field Selection**: Chilli growing fields were selected from different parts of Bangladesh to cover variation in disease intensity, environmental conditions, and farming practices.
- • **Leaf Collection**: Chilli leaf samples were collected in groups according to the color of their leaf spots and properties (healthy leaves and diseased leaves). Photos were taken of healthy and

infected leaflets from both pathogens on non-treated plants.

- • **Image Capturing**: Natural light high-resolution images were captured to obtain clear views with minimal shadows, glare, and reflections, enabling better visualization of disease patterns including discoloration, lesions, pest damage, and fungal growth.
- • **Image Organization**: The acquired images were stored in a central image repository with well-structured directories to ensure efficient data management and processing.
- • **Image Resizing**: All images were resized to a uniform resolution of 1000 × 1000 pixels to match the input dimensions required by the selected CNN architectures.
- • **Image Labeling**: Each image was labeled into 6 categories: Bacterial Sport, Cercospora Leaf Sport, Curl Virus, Nutrition Deficiency, Powdery Mildew, and Healthy leaves
- • **Classification Preparation**: The labeled images were organized into class-wise folders to facilitate automatic data loading and effective training of deep learning models.

This design of the preprocessing and classification pipeline provides good-quality input data and a match for accurate multi-class chilli leaf disease detection through CNN.

2.4. Techniques of Image Augmentation

Image augmentation was used to improve the invariance and generalization of deep learning models when working with real chilli leaf disease data. The real data was class-imbalanced and invariant to natural variations of in illumination, orientation, and image background. So, it is required to augment the data to enhance practical applications. The applied techniques included horizontal and vertical flipping, random rotation within − 45° to + 45°, scaling between 0.8 and 1.2, Gaussian blurring with values from 0.5 to 2.5, contrast adjustment in the range of 0.7 to 1.3, shearing between − 0.3 and + 0.3, zooming up to 1.5× with cropping, and uniform random noise addition from − 60 to + 60.

The legitimate 16,392 images were augmented and balanced into 6 classes, with each containing 2,732 images, through these operations. This approach mitigated class imbalance, enhanced data diversity and generalization, and alleviated overfitting, thereby providing robustness for accurate multi-class recognition of chilli leaf disease in practical agricultural scenarios. The augmentation not only handled class imbalance but also introduced significant variability to the dataset. Then the deep learning models trained on this augmented dataset would be less susceptible to overfitting and better at generalizing to real-world situations. The augmented dataset was essential for training accurate, robust models for early detection of multi-class chilli leaf disease, enabling precision agriculture through remote sensing technology and indirectly reducing crop diseases.

Table 2
Number of Original and Augmented Images in the Chili Leaf Dataset

Serial No.	Class Name	Original Images	Augmented Images	Total Images
1	Bacterial Sport	1303	1429	2732
2	Cercospora Leaf Sport	1518	1214	2732
3	Curl Virus	1272	1460	2732
4	Healthy	1318	1414	2732
5	Nutrition Deficiency	966	1766	2732
6	Powdery Mildew	674	2058	2732
Total		7051	9341	16,392

2.2. Dataset Structure

The chilli leaf disease dataset is organized in a hierarchical directory structure for efficient data handling and model training. It is divided into two main folders such as Original Images, containing raw field-captured chilli leaf images and Augmented Images consisting of synthetically generated samples used to balance classes and increase data diversity. Each folder includes six class-specific subdirectories covering five disease categories and healthy leaves. All images were resized and normalized prior to training to ensure consistency.

4. Results

The five CNN models had good performance with regard to classifying the chilli leaf conditions. MobileNet provided the best and trustworthy prediction followed by EfficientNetB3 and ResNet50. The general conclusions suggest the responses to the efficiency of deep learning in the automation of identifying diseases in agricultural fields.

3.1. Model Validation

To demonstrate the effectiveness of our proposed chilli leaf disease classification framework, five popular pretrained convolutional neural network models, DenseNet121, EfficientNetB3, MobileNet, ResNet50, and InceptionV3, were tested by their respective prediction performance over six classes on chilli leaves, which include multiple disease conditions and healthy leaves. These models were chosen for their demonstrated efficacy in image classification tasks and their appropriateness for the comparison. All models were trained with a batch size of 32 for 25 epochs using the Adam optimizer and an initial learning rate of 0.001 to ensure robust convergence and avoid overfitting.

The preprocessed chilli leaf image dataset 16,392 images was split into an 80:20 ratio for training and validation to test model generalization during training. During the training, the accuracy and loss curves for both the training and validation sets were checked. These plots are invaluable for understanding your model's behavior as it learns, including overfitting/underfitting (the case where the training accuracy goes up while validation performance goes down). Get too wide. Ideally consistent trends across the training and validation curves indicate the model's ability to generalize well to new data.

The performance of the models was assessed by using standard classification metrics such as accuracy, precision, recall, and F1-score. These metrics provide a more complete overview of classification performance, especially in multi-class problems where class imbalance is not accounted for. Precision (positive prediction), recall (relevant disease instances), and the F1-score trade off both precision and recall. Accuracy (average) refers to the ratio of correctly classified samples across all classes. The application of validation curves and the selection of evaluation metrics ensure robust model performance and help identify the optimal deep learning architecture for early detection of multi-class chilli leaf disease. The particular formula for calculating these metrics is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Accuracy} = \frac{TP}{TP + FN}$$

F1-score = 2 × (Precision × Recall) / (Precision + Recall)

with TP, TN, FP, and FN being True Positives, True Negatives, False Positives and False Negatives, respectively.

Table 3 shows the performance of the MobileNet model when it classifies chilli leaves into six categories namely: Bacterial Sport, Cercospora Leaf Sport, Curl Virus, Nutrition Deficiency, Powdery Mildew, and

Healthy leaves. It achieves an accuracy of 96.00%. Figure 5 plots the MobileNet loss and accuracy curve, and Fig. 6 the MobileNet confusion matrix.

Table 3
Performance Evaluation of the Proposed Model for Chili Leaf Disease Classification

Class Name	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Bacterial Spot	96	96	96	96
Cercospora Leaf Spot	98	96	97	96
Curl Virus	92	95	93	96
Healthy	94	95	94	96
Nutrition Deficiency	98	96	97	96
Powdery Mildew	100	100	100	96

Table 4
Performance Comparison of Deep Learning Models

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
MobileNetV2 (Proposed)	96	96	96	96
ResNet50	95	95	95	94
DenseNet121	95	95	95	94
EfficientNetB0	93	92	92	92
InceptionV3	10	17	9	19

5. Discussion

The discussion section should interpret and explain the findings in relation to the research objectives and existing literature introduced in the Introduction section. Similarities or differences with previous studies should be highlighted, and the theoretical, practical, or policy relevance of the findings should be discussed with reference to sustainable development.

6. Conclusion

This research proposed a deep learning approach for the early detection of multiclass chilli leaf diseases in authentic field images. To validate the proposed approach, a large dataset of diseased chilli leaves containing 8,814 high-resolution images, divided into 6 classes (diseased and healthy), was built to test several pre-trained CNN models. By incorporating systematized preprocessing, data augmentation, and transfer learning, the proposed method successfully mitigated the visual similarity across diseases and environmental variations.

The experimental results showed that MobileNet achieved the highest performance among a group of other models, with an overall classification accuracy of 96% and balanced values for precision, recall and F1-Score. The results demonstrate that deep learning can be effectively applied to accurately and automatically detect chilli leaf disease in the field using real time images. The developed system is expected to be of great interest to precision agriculture and can contribute to early-stage disease monitoring and better crop management, leading to less yield loss.

In future work, the dataset can be expanded, the method extended to account for time or multiple spectral bands and applied on mobile or embedded platforms for real-time field surveillance.

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Figures

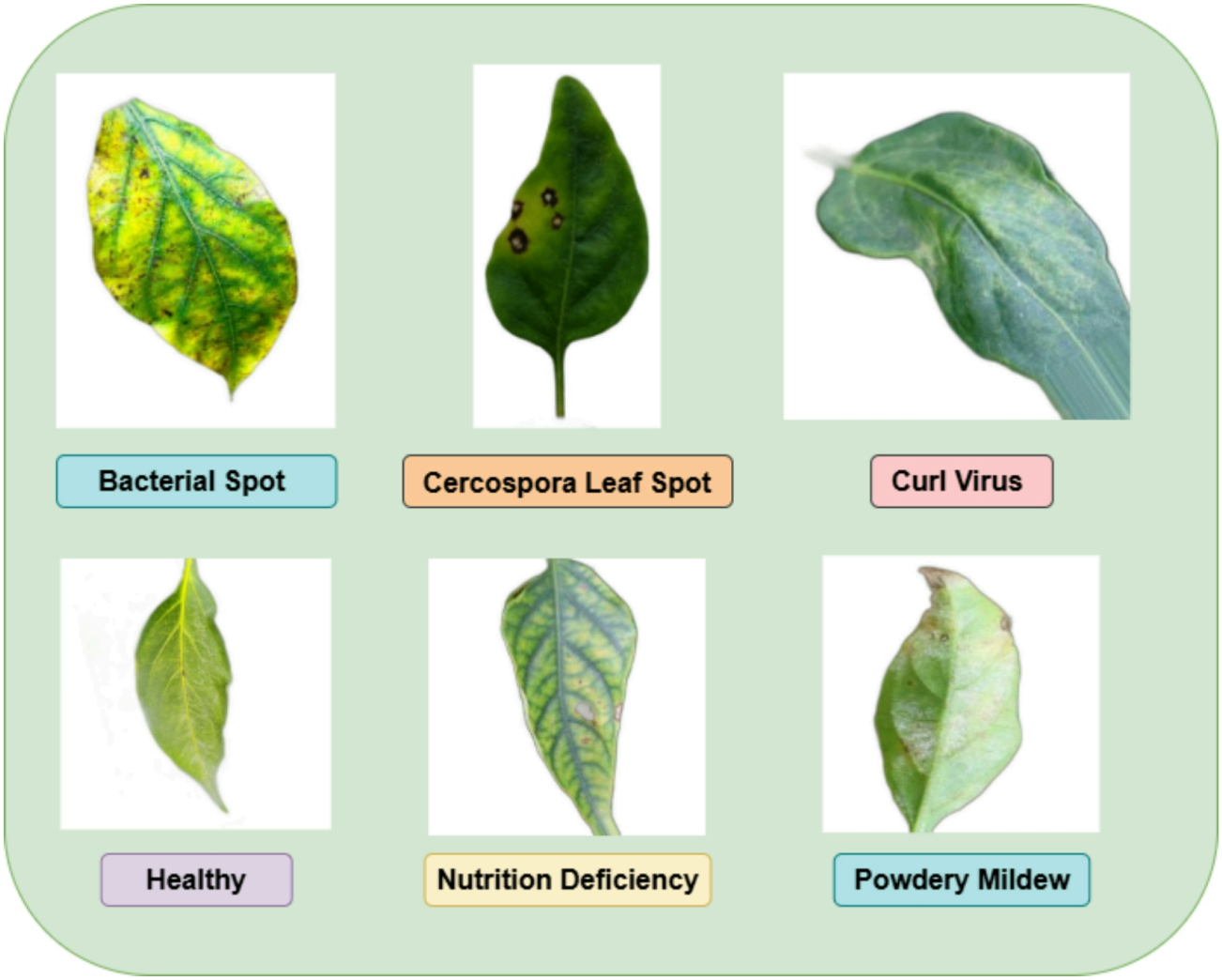


Figure 1

Sample Images from the Chilli Leaf Disease Dataset.

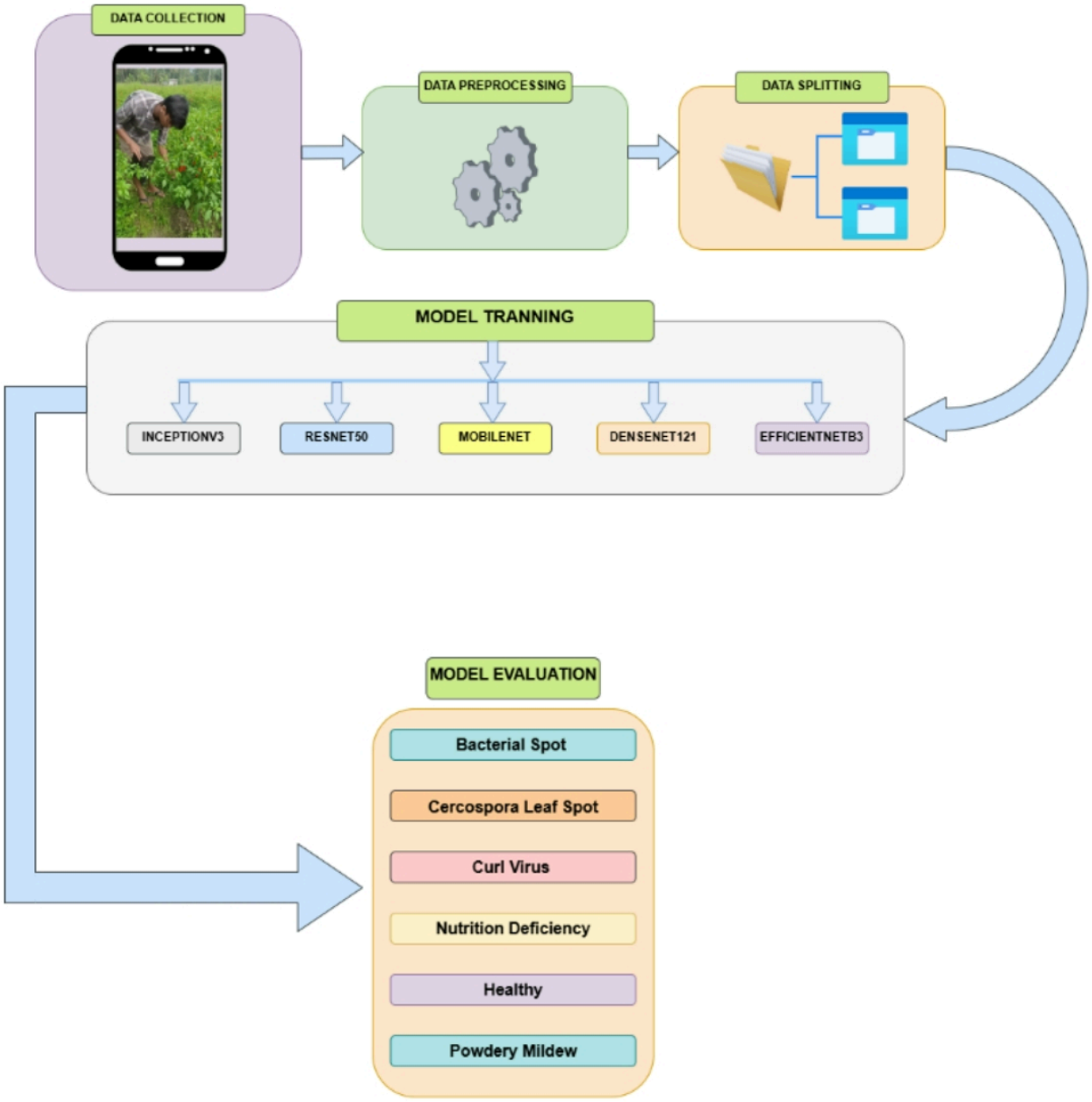


Figure 2

Flowchart for Early Detection of Chilli Leaf Diseases.

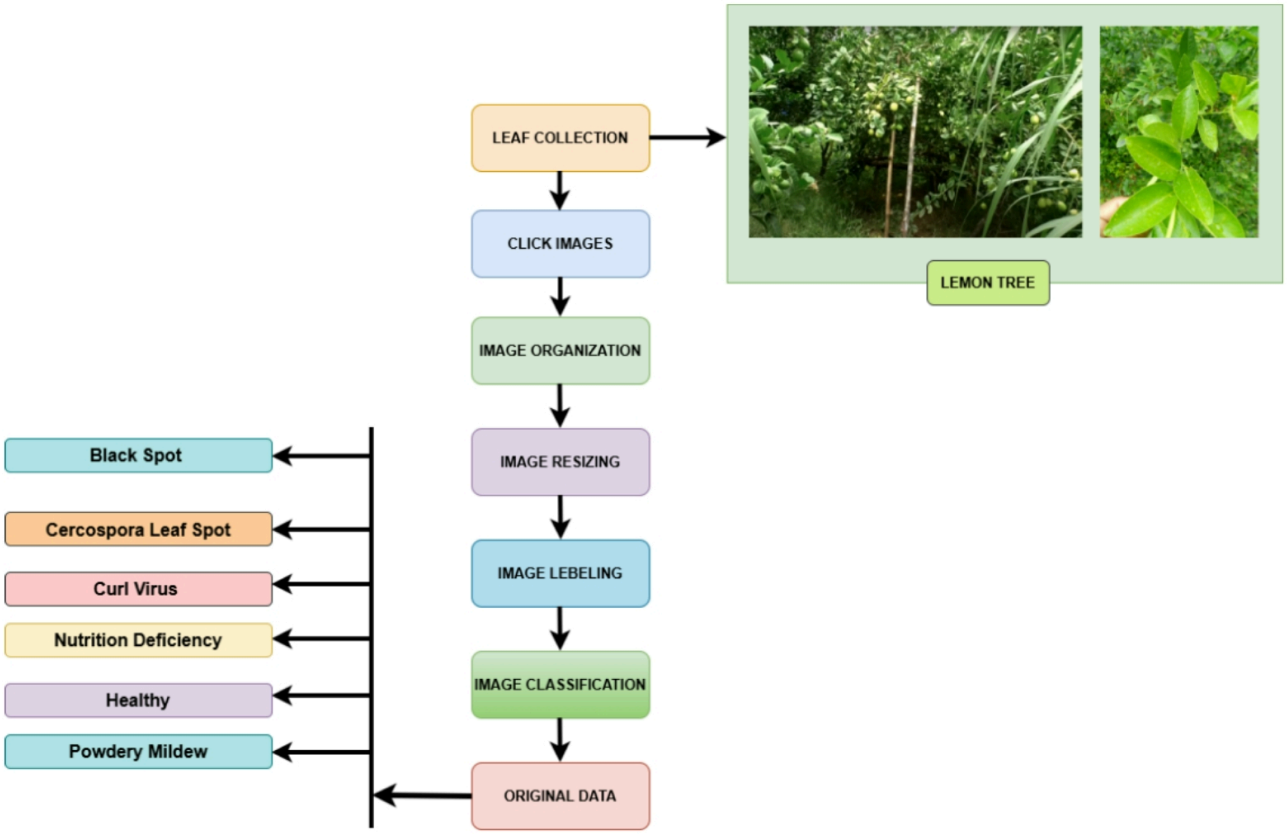


Figure 3

Workflow of image pre-processing and classification.

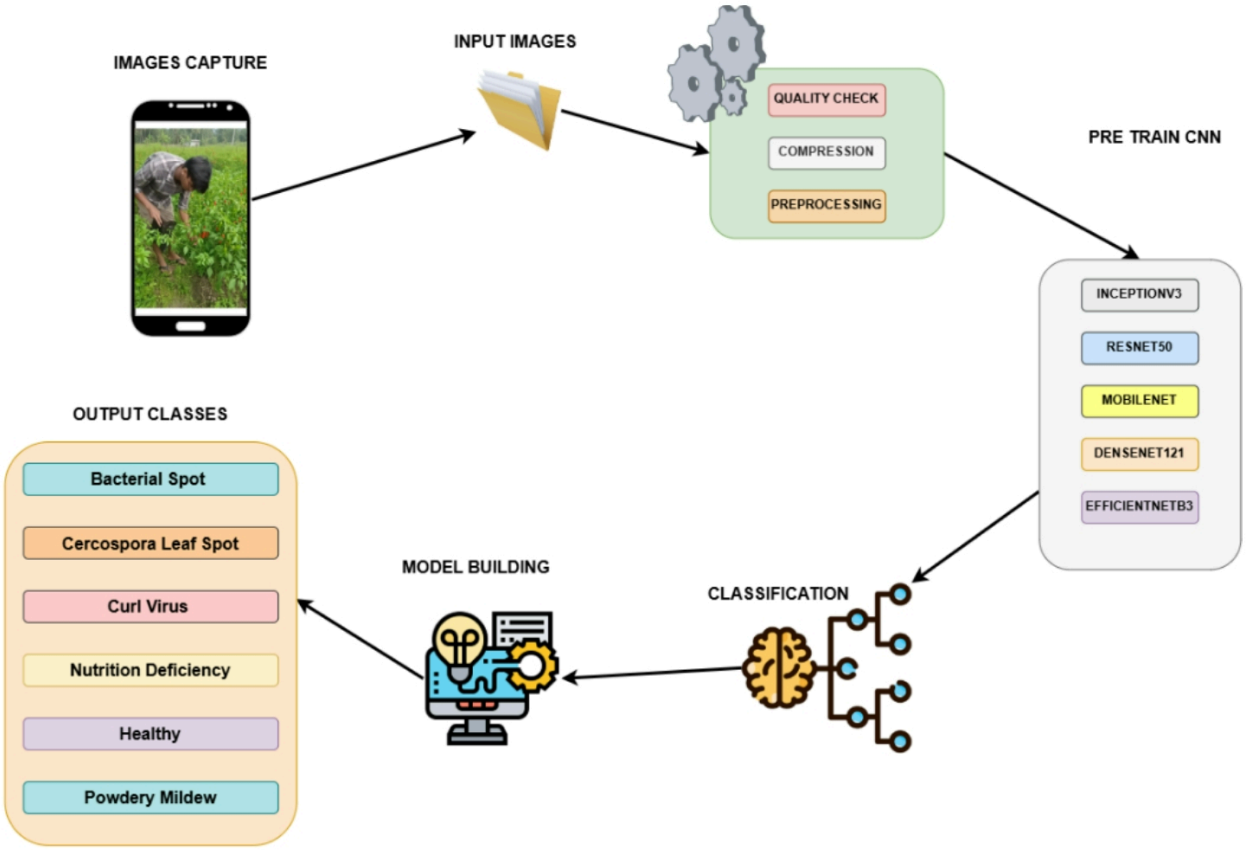


Figure 4

The visual abstract for Chilli Leaf classification.

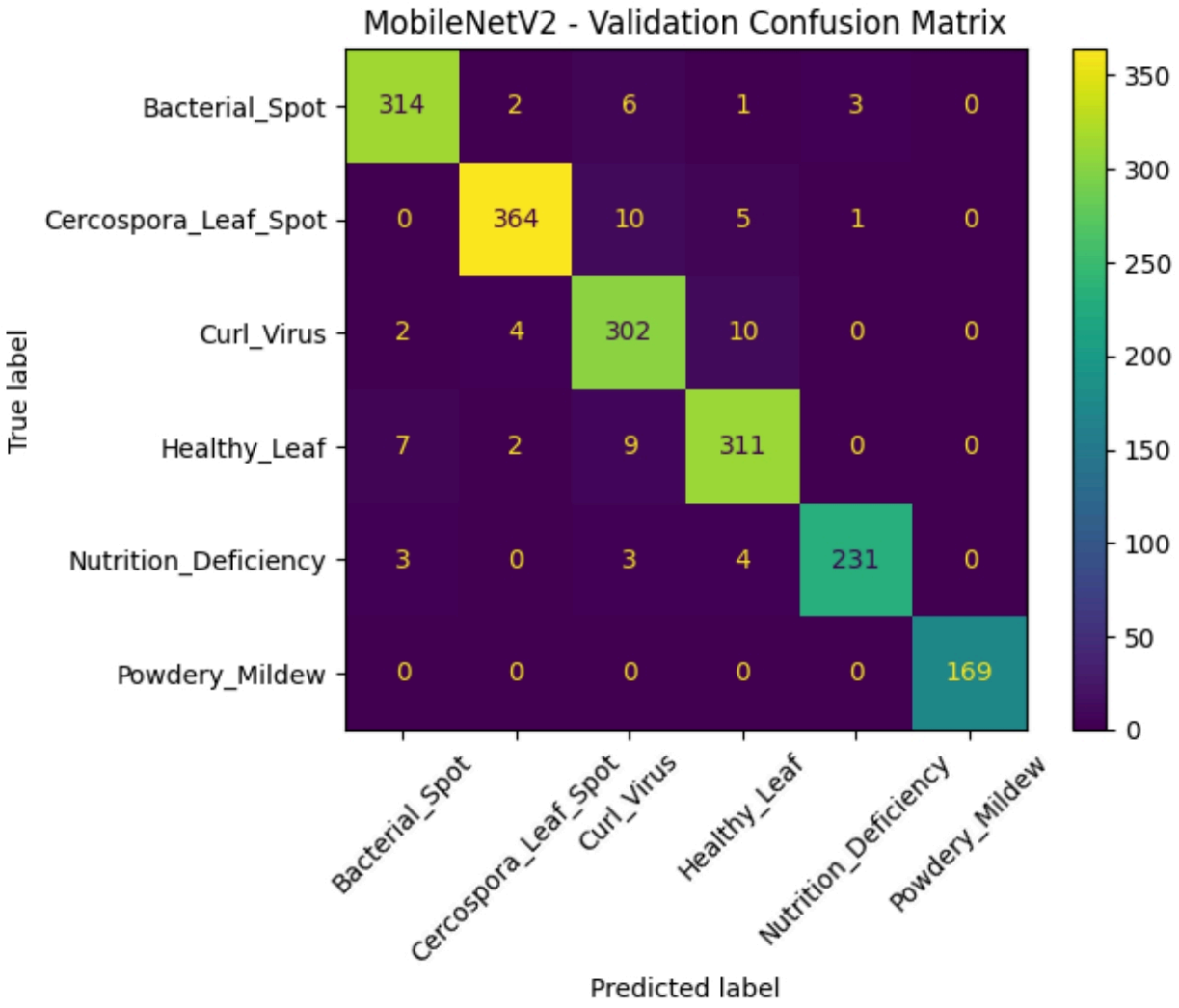


Figure 5

The visual abstract for Chilli Leaf classification.

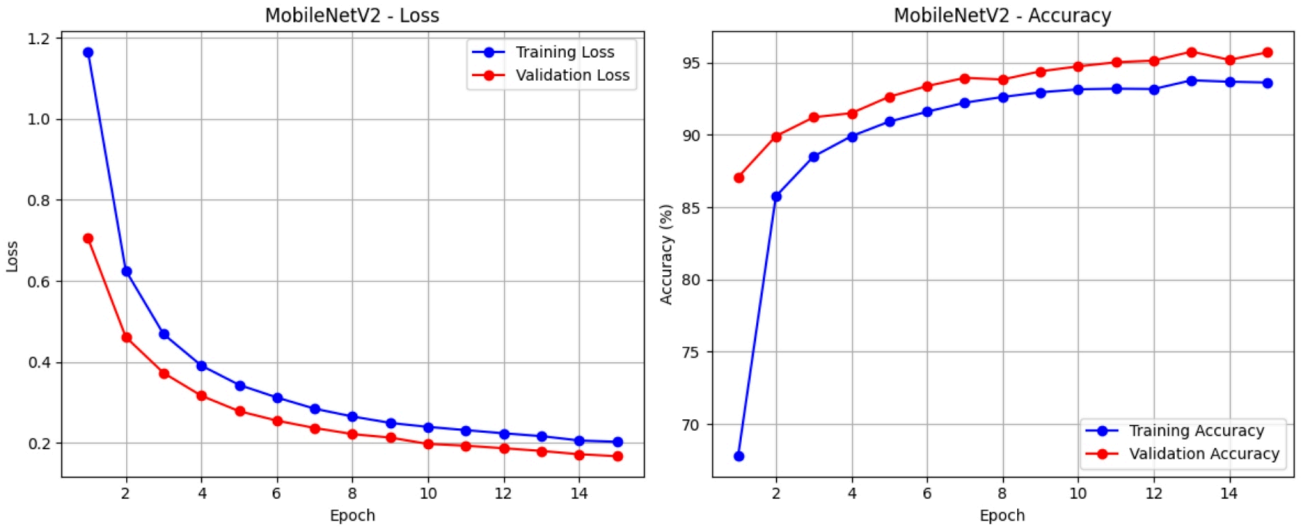


Figure 6

Accuracy and loss curve for MobileNet model