



## Chili Leaf Disease Detection Using Deep Feature Extraction

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### Abstract

Diseases in crops lead to decreased production, which can be addressed through consistent surveillance. Manual surveillance of crop diseases is both arduous and prone to mistakes. The timely identification of crop leaf diseases using Computer Vision and Artificial Intelligence can aid in minimizing the negative impact of diseases and address the limitations of continuous human surveillance. To classify chili crop diseases, this research paper introduces a new deep feature extraction model based on Transfer Learning using ResNet50, MobileNet, EfficientNetB0, and multiple classifiers. On Plant Village dataset related to the diseases of the chili crop and Private data set, the proposed method was trained and tested. And analyzed the results by comparing the performance of the pre-trained deep learning models on original data and data filtered through the Image filtering mechanisms and proposed method on the plant village dataset and private dataset, the highest performance accuracy is 99.6% with ResNet50 and the faster CPU time for feature extraction is 29.3 seconds using MobileNet. Comparing the suggested model to the most advanced deep learning models reveals greater accuracy with fewer computational resources.

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**Keywords:** Plant disease detection; MobileNet; ResNet; EfficientNet; Transfer Learning; Deep feature extraction; chili diseases

### 1. Introduction:

India holds a prominent position as a major commercial producer of chili, being the world's leading producer, consumer, and exporter of this popular spice. In the financial year 2018-19, the value of chili exports from India amounted to Rs. 5930.12 crore. Remarkably, this value doubled to Rs. 10773.59 crore in the financial year 2022-23 [1]. However, the chili crop is susceptible to various diseases that can cause significant damage. Recognizing these diseases at an early stage and implementing appropriate corrective measures are crucial for preserving the yield and quality of the crop. Symptoms of chili diseases typically manifest on various parts of the plant, with the leaves often displaying visible signs such as changes in color, the presence of spots, and blight. Machine learning (ML) and deep learning (DL) algorithms have revolutionized the area of computer vision, representing the forefront of image detection methods. In traditional computer vision approaches, human experts play a vital role in selecting relevant features for diagnosing plant diseases. However, with the emergence of Deep Learning (DL) techniques, which encompass thousands or even millions of adjustable parameters, significant advancements have been achieved in image classification.

DL techniques have proven to be highly effective and currently yield the best results in this domain. Their ability to automatically learn from and adapt from large datasets has propelled them to the forefront of image classification

techniques. A range of widely used deep learning pre-trained models, including AlexNet, GoogleNet, LeNet, VGGNet, ResNet, Inception, NasNet, SqueezeNet, DenseNet, EfficientNet, and MobileNet, have been employed for the precise identification of plant diseases. These models [2] play a crucial role in advancing the field of agricultural disease diagnosis.

The objective of the proposed method is to tackle the challenge of classifying multiple chili crop leaf diseases using Transfer learning (TL). The proposed approach utilizes pre-trained deep learning models to extract features and employs multiple classifiers for the classification process. This methodology aims to enhance the accuracy and efficiency of disease classification in chili crops, utilizing both public i.e., Plant Village dataset [3] and private datasets.

This research introduces a novel approach for classifying diseases in chili crops using both public (Plant Village) and private datasets. The private dataset consists of chili leaf images captured after 120 days of growth in Zaffergadh, India, and underwent essential image pre-processing steps such as resizing, background removal, and rotation. To extract features, popular neural network architectures like ResNet50, MobileNet, and EfficientNetB0 are employed, along with a range of classifiers including Classification and Regression Tree (CART), Logistic Regression (LR), Naive Bayes (NB), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), Gradient Boosting (GB), Adaboosting (ADA) and Multi-Layer Perceptron (MLP). The study further explores the impact of image filters, specifically Gaussian and Unsharp filters, selected for their superior PSNR and SSIM values among five filters. Performance metrics encompass Accuracy, Precision, Loss, F1-Score, Specificity, Sensitivity, and Recall. Additionally, this research considers CPU time, addressing resource limitations for practical implementation.

## 2. Related Work

Barbedo and Jayme [4] investigate the utility of individual lesions for disease identification, improving data variability without additional images and enabling the detection of multiple diseases. This method achieves 12% higher average accuracies compared to using original images, maintaining accuracies above 75% even with up to 10 diseases. In preparation for training, all images were resized to meet the requirements of GoogLeNet, which are 224 x 224 x 3 pixels. Experiments are divided into two groups, one focusing on classifying observed symptoms, and three sets of images are employed for each crop. Another experiment evaluates severe class imbalance by augmenting image sets to achieve equal samples for all diseases, comparing results with unbalanced data. This article offers a way to substantially increase the diversity and size of datasets.

Militante et al. [5] proposed a system to detect approximately 35,000 images of various plant leaf diseases. Data augmentation is used to improve the dataset. The model achieved a training accuracy of 96.5% after 75 epochs and a maximum accuracy of 100% when testing with random images. Future work could involve expanding the dataset with more plant varieties and diseases and experimenting with different CNN architectures, learning rates, and optimizers to improve model performance and accuracy.

Mohameth et al. [6] evaluated the application of CNN with TL and deep feature extraction using the PV Dataset. The features obtained from the models are classified using SVM and KNN, with the results indicating SVM as the best classifier for crop leaf disease recognition. ResNet50 outperformed VGG16 and Google Net in terms of feature extraction.

Ashok et al. [7] employed image pre-processing to enhance tomato leaf images by reducing noise and blur using a Gaussian filter. Feature extraction is performed using DWT and GLCM, utilizing sub-bands and correlation coefficients to classify leaf images based on luminous levels. A CNN algorithm is used for hierarchical feature extraction, mapping pixel values, and classifying them through fully connected layers. The proposed approach achieves a high accuracy of 98.12%, outperforming AlexNet and ANN models.

Chowdhury et al. [8] developed a deep learning architecture based on EfficientNet for classifying tomato leaf diseases using plain and segmented leaf images. The modified U-net segmentation model achieves high accuracy for segmenting leaf images. EfficientNet-B7 performs well in binary and six-class classifications with segmented images, while EfficientNet-B4 excels in ten-class classifications. The models show improved performance when trained on segmented images, with EfficientNet-B7 and EfficientNet-B4 delivering the best results for different classification tasks.

Bedi, Punam, and Gole, Pushkar [9] proposed a DL model for plant disease recognition that decreases the count of training parameters by employing a dimensionality reduction technique called CAE before classification using CNN. This model attains a testing accuracy of 98.38%, outperforming several existing research studies while using significantly fewer training parameters. Although the testing accuracy is a little lower than some state-of-the-art

systems, this model offer faster training and prediction times due to its reduced parameter count. This makes it suitable for automatic plant disease recognition on low-computation devices.

Paymode, Ananda, and Malode, Vandana [10] proposed a method for the detection and classification of grape and tomato diseases using CNN methods for identifying Multi-Crops Leaf Disease and extracting image features using a deep learning model to classify healthy and diseased leaves. Authors employ the VGG model for improved performance scores. The model achieves high accuracy in classifying disease-affected leaves, with 98.40% accuracy for grapes and 95.71% accuracy for tomatoes.

S. M. Hassan and A. K. Maji [11] built a novel DL model utilizing the inception and residual connection, with depth wise separable convolution to decrease parameters. The model achieves high accuracy on 3 plant disease datasets: 99.39% on Plant Village, 76.59% on the imbalanced cassava dataset, and 99.66% on Rice. Compared to other DL architectures, the proposed method has lesser parameters and faster performance. The model demonstrates robustness and satisfactory performance on various plant disease datasets, indicating its effectiveness in disease detection.

Saeed et al. [12] proposed a model aimed at diagnosing tomato diseases using Inception V3 and Inception ResNet V2. These models were trained on a combination of PV dataset and real time images, totaling 5225 images. Dropout rates ranging from 5% to 50% were investigated, and performances were achieved with the Inception V3 and Inception ResNet V2 using a 50% dropout rate and the model using a 15% dropout rate. Both models achieved an accuracy of 99.22% and a loss of 0.03, indicating their competitiveness and high accuracy in diagnosing tomato leaf diseases.

Arumuga Arun et al. [13] present the Complete Concatenated Deep Learning architecture, a multi crop class detection model capable of classifying crop diseases across different crops. The architecture introduces the Complete Concatenated Block as a core functional unit, utilizing point convolution layers to reduce model parameters. The complete concatenation path enhances feature map utilization for improved classification accuracy. This architecture is trained and pruned to create the Pruned Complete Concatenated Deep Learning model, with the PCCDL-PSCT variant achieving the highest classification accuracy of 98.14% and a reduced model size of approximately 10 MB.

### 3. Methodology

#### 3.1 Data Sources

**Public Data (Plant Village):** Likely contains a diverse set of chili crop images, providing a foundation for the study. It contains 2 classes namely Pepper\_bell\_Bacterial\_spot (PVD), Pepper\_bell\_healthy (PVH).

**Private Data:** These are images captured in a specific location (Zaffergadh, Telangana, India) and aged 120 days. The inclusion of private data can help account for local variations in disease patterns. It contains 5 classes namely Bacterial Leaf Spot (PD1), Curl (PD2), Fusarium (PD3), Healthy (PH), Pests (PD4). Both the data sources are represented in Table 1.

#### 3.2 Data Pre-processing

**Image Pre-processing:** This includes essential steps such as resizing, background removal, and image rotation. These steps ensure that the data is in a suitable format for analysis and modelling. The research evaluates the impact of image filters, particularly Mean, Median, Gaussian, Gabor and Unsharp filters [14], on model performance. The Gaussian and Unsharp filters are chosen based on their ability to enhance image quality, as indicated by PSNR and SSIM values. This step enhances the robustness of the classification approach.

#### 3.3 Feature Extraction

Convolutional Neural Networks (CNN) [15] are effective in computer vision tasks, automatically extracting features from training images. They consist of convolutional, pooling, and fully connected layers. The convolutional layer extracts features using kernels and produces feature maps. Pooling layers decreases the dimension of feature maps. Fully connected layers connect inputs to outputs by weights, and the final layer contains the equal number of outputs as classes.

Transfer Learning [16] is a popular method in computer vision that involves sharing knowledge from one problem to solve similar problems. It reduces training time when domains are similar. There are two approaches: 1) Using pre-trained models, trained on large datasets like ImageNet [17] for general classification tasks. 2) Defining a customized output layer by excluding the pre-trained model's output layer and using it as a feature extractor [18] for specific classification tasks. The custom model is then trained to improve classification results. The proposed study leverages pre-trained deep learning models like ResNet50 [19], MobileNet [20], and EfficientNetB0 [21] for feature extraction. Transfer learning is a powerful technique to harness knowledge from these well-trained models, potentially improving the classification task's performance.

### 3.4 Classifiers

A wide array of classifiers is employed, spanning from traditional machine learning techniques like CART, LR, NB, LDA, SVM, KNN, RF, GB, and ADA [22] to deep learning with MLP. This diversity in classifiers helps evaluate which methods perform best for chili disease classification.

### 3.5 Performance Metrics

This study employs a comprehensive set of performance metrics like Accuracy, Precision, Loss, F1-Score, Precision, Specificity, Sensitivity and Resource Consideration. The inclusion of CPU time as a metric highlights the practicality and efficiency of the proposed approach. This is especially important for real-world applications where computational resources might be limited.

## 4. Results and Discussion

In this section, the experiments were trained and tested in 2 ways in a Laptop with AMD Ryzen 5 4600H with Radeon Graphics, 3000 MHZ, 6 cores, 12 logical processors, 32 GB of RAM, and NVIDIA® GeForce® GTX 1650Ti graphics. Firstly, TL with MobileNet, ResNet50, and EfficientNetB0 on three datasets based on PV includes Original (PV\_Original), Gaussian filtered (PV\_GF), and Unsharp filtered (PV\_UF). PV\_GF and PV\_UF datasets were created by applying corresponding image filtering mechanisms as these scored highest PSNR and SSIM values among mean, median and Gabor filters represented in Table 2. Then, next experiment includes deep feature extraction with MobileNet, ResNet50 and EfficientNet, classification [22] with CART, LR, NB, LDA, SVM, KNN, RF, GB, ADA and MLP on PV and private dataset. The experimental results are shown in Table 4 and 5.

Table 1: Dataset details

Public-Plant Village (2475)			Private (671)			
PVD	PVH	PD1	PD2	PD3	PH	PD4
997	1478	102	159	139	179	92

Table 2: Applying Filters on Public Data set (Healthy and Bacterial Leaf Spot)

Filter	Healthy		Bacterial Leaf Spot	
	PSNR	SSIM	PSNR	SSIM
Mean	30.566	0.63	31.161	0.642
Median	30.026	0.459	30.447	0.483
Gaussian	30.61	0.654	31.199	0.664
Unsharp	33.339	0.936	34.063	0.937
Gabor	28.004	0.274	27.838	0.276

In the proposed approach, the training and testing ratios of 2 experiments are 70:30 and 75:25. The hyper parameters for the both the experiments include Adam Optimizer, 20 epochs, the learning rate is 0.001, drop out is 0.2, and the batch size is 32 and 16.

Table 3: Accuracies of Pre-Trained models on PV dataset

Dataset	EfficientNetB0	ResNet50	MobileNet
PV_Original	98.4	99.6	98.8
PV_GF	95.7	98	97.5
PV_UF	96.9	99.22	98.4

From Table 3, for the PV dataset, ResNet50 shows the highest performance with an accuracy of 99.6%, followed by MobileNet with an accuracy of 98.8%. EfficientNetB0 has the lowest performance among the three models, with an accuracy of 98.4%. The PV\_UF data set achieves higher performance compared to the PV\_GF data set.

In Table 4, each row represents a different model's performance measures includes Accuracy, Precision, loss, F1 score, Specificity, Sensitivity, and the columns show the classifier type for each model for the . It is observed from the table that with the MobileNet deep extraction model, SVM and LR seem to be the most promising models, while MLP performs the worst based on the metrics. By considering ResNet50 deep extraction model, the performances of LR, SVM, and ADA show promising results, while LDA show relatively lower performance. In Table 5, ResNet50

outperforms MobileNet across all machine learning models in terms of accuracy on the private dataset. LR, RF and Multi-layer Perceptron (MLP) seem to be the top-performing models for both MobileNet and ResNet50, with LR achieving the highest accuracy for both. It is also observed from the table 4 and 5 ResNet50 is most accurate model to classify chili leaf diseases. The faster CPU time for feature extraction is 29.3 seconds using MobileNet represented in Table 6. Figure 1 (a), (b) and (c) represents accuracy and loss for training and validation sets. In Figure 2, the x and y axis of the graph represents accuracy and classifier.

Table 4: Performance measures of proposed method on various classifiers for the PV data set

Model	Performance Score	Classifiers									
		LR	LDA	CART	NB	SVM	RF	KNN	GB	ADA	MLP
MobileNet	Accuracy	96.36	91.91	78.98	87.87	97.57	91.91	94.94	90.3	91.7	60.6
	Precision	0.97	0.93	0.85	0.91	0.97	0.89	0.94	0.88	0.94	0.61
	Loss	1.31	2.91	6.99	4.37	0.87	3.06	1.82	3.5	2.99	14.2
	F1 score	0.97	0.93	0.84	0.9	0.98	0.93	0.96	0.92	0.93	0.75
	Specificity	0.97	0.89	0.74	0.86	0.96	0.82	0.93	0.86	0.89	0.96
	Sensitivity	0.97	0.94	0.82	0.89	0.99	0.98	0.97	0.95	0.95	0.96
ResNet50	Accuracy	99.52	89.98	95.80	91.60	99.35	96.93	97.58	97.09	99.35	98.87
	Precision	0.99	0.89	0.98	0.95	0.99	0.96	0.97	0.97	0.99	0.99
	Loss	0.17	3.61	1.11	3.03	0.23	1.16	0.87	1.05	0.23	0.41
	F1 score	0.99	0.92	0.97	0.93	0.99	0.97	0.98	0.98	0.99	0.99
	Specificity	0.99	0.83	0.91	0.93	0.99	0.93	0.95	0.96	0.99	0.99
	Sensitivity	0.99	0.95	0.97	0.90	0.99	0.99	0.99	0.98	0.99	0.99
EfficientNetB0	Accuracy	94.8	91.5	79.03	85	93.15	85	90.7	87.5	89.52	95.2
	Precision	0.96	0.93	0.83	0.87	0.94	0.82	0.9	0.85	0.91	0.97
	Loss	1.89	3.05	7.85	5.38	2.47	5.52	3.34	4.51	3.78	1.74
	F1 score	0.96	0.93	0.81	0.88	0.94	0.88	0.92	0.9	0.91	0.96
	Specificity	0.94	0.89	0.78	0.8	0.91	0.68	0.84	0.76	0.87	0.96
	Sensitivity	0.95	0.93	0.81	0.88	0.95	0.96	0.95	0.95	0.91	0.95

Table 5: Accuracies of proposed method on various classifiers for the Private data set

Model	LR	LDA	CART	NB	SVM	RF	KNN	GB	ADA	MLP
MobileNet	85.12	69.88	70.57	72.64	78.57	76.19	77.98	70.83	72.98	77.81
ResNet50	90.48	76.79	77.29	81.55	87.5	88.1	85.12	77.98	81.07	88.1

Table 6: Resource Utilization of various models using proposed method

Deep feature Extraction Model	Class	Batches	Time per Step	Total CPU Time	Total Wall Time
ResNet50	Bacterial_leaf_spot	63/63	45s 683ms	37.6s	44.9s
	Healthy	93/93	68s 728ms	59s	1min 7s
MobileNet	Bacterial_leaf_spot	63/63	12s 180ms	7.64s	12.1s
	Healthy	93/93	17s 183ms	11.2s	17.2s
EfficientNetB0	Bacterial_leaf_spot	63/63	14s 213ms	8.95s	14.3s
	Healthy	93/93	19s 200ms	11.3s	18.7s

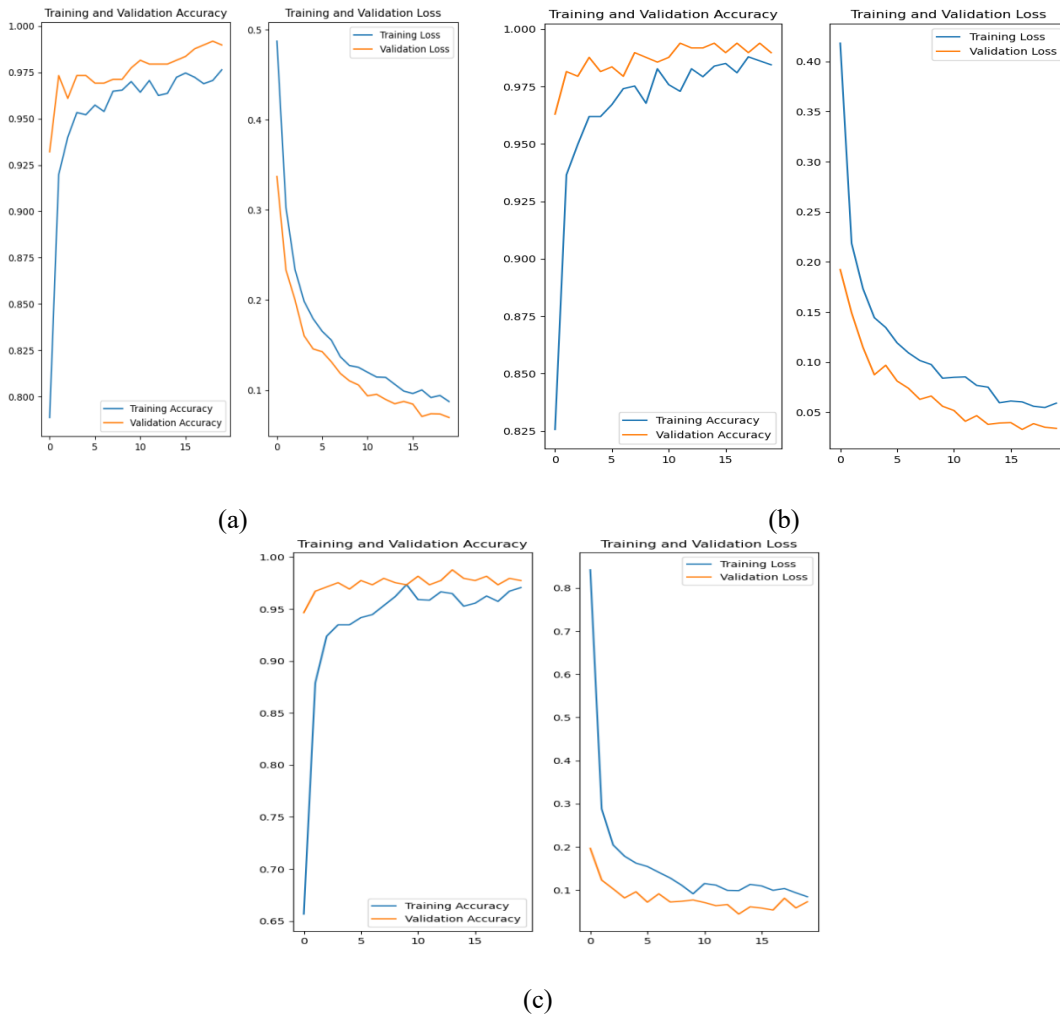


Figure 1: Training and Testing Accuracy and Loss curves (a) EfficientNetB0 (b) ResNet50 (c) MobileNet

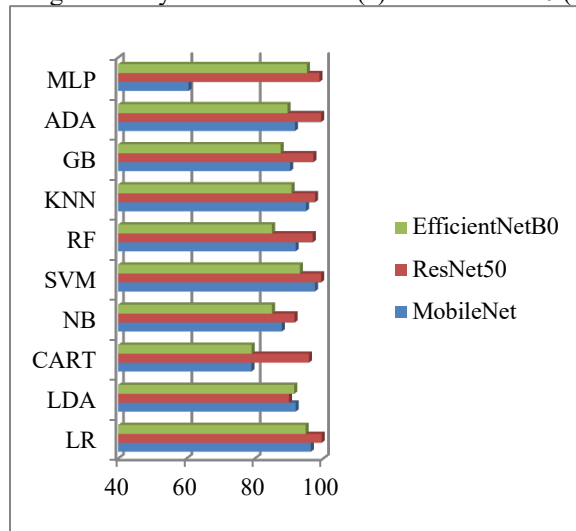


Figure 2: Accuracies of various classifiers

## 5. Conclusion and Future works

The detection of plant diseases in their early stages poses a considerable challenge for researchers. Various ML and DL techniques have been explored to automate the procedure of crop leaf disease detection. In this paper, a novel hybrid model is proposed for automatic crop leaf disease detection, leveraging transfer learning on the PV dataset of the chili class. The proposed model attains an impressive testing accuracy of 99.59% by employing deep feature extraction with ResNet50 and Adaboost classifier. It highlights the superior performance of the proposed hybrid model based on ResNet50. Furthermore, this paper conducts a comparative analysis of the performance of EfficientNetB0, MobileNet, and ResNet50 models in the context of 3 datasets, including Original, Gaussian Filtered and Unsharp Filtered. MobileNet has also given notable accuracy and easily fits into smart computing devices. In future research, a significant reduction in training parameters is anticipated, which will greatly reduce the time required for model training in automatic plant disease detection. Consequently, the trained model will be capable of efficiently identifying diseases in plants within a shorter time frame.

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