



## Plant Disease Classification Using Deep Learning Driven by Lesion-Focused Next-Generation Segmentation

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**Abstract:** Plant disease detection using leaf images has become a critical component of precision agriculture, enabling timely intervention and improved crop management. This study presents a deep learning-based framework for accurate and robust plant disease classification. A novel dataset, EruCauliflower DB, was developed, comprising high-resolution images of cauliflower leaves affected by *Alternaria* Leaf Spot (114 images) and Black Rot (99 images). The proposed framework consists of three stages. First, a novel lesion-focused segmentation technique, BorB, is introduced to effectively isolate diseased regions by combining Lab and RGB color space features through a logical OR operation. Second, data augmentation techniques, including geometric transformations, are applied to enhance data diversity and improve model generalization. Finally, four deep learning models VGG16, ResNet50, EfficientNetB3, and MobileNetV3 Large—are employed for classification. Experimental results demonstrate that the proposed system achieves 100% classification accuracy on the Eru Cauliflower DB dataset across all models. The framework is further validated on the Mango Leaf BD dataset, also achieving 100% accuracy, and on 15 classes from the Plant Village dataset, reaching 99.78% accuracy. These results highlight the effectiveness, robustness, and generalization capability of the proposed approach, making it suitable for real-world agricultural applications.

**Key Words:** Agriculture, BorB image segmentation, data augmentation, deep learning, EruCauliflowerDB, leaf disease detection

### 1. Introduction

Agriculture plays a crucial role in ensuring food security and supporting the economic development of many countries. As the global population continues to grow, the

demand for food production is increasing significantly. However, plant diseases remain one of the major challenges affecting agricultural productivity and crop quality. Diseases caused by fungi, bacteria, and other

microorganisms can severely damage crops, leading to significant economic losses for farmers and agricultural industries. Early detection and accurate identification of plant diseases are therefore essential for improving crop yield and ensuring sustainable agricultural practices.

Traditional methods for detecting plant diseases rely heavily on manual inspection by agricultural experts. These methods are often time-consuming, labor-intensive, and expensive. Additionally, farmers in remote or rural areas may not have access to expert diagnosis, which delays disease detection and treatment. With the rapid advancement of artificial intelligence, image processing, and deep learning technologies, automated plant disease detection systems have become an effective alternative for monitoring plant health and supporting precision agriculture. Deep learning techniques, especially convolutional neural networks (CNNs), have shown excellent performance in plant disease detection from leaf images. However, real-world challenges such as varying lighting, shadows, and complex backgrounds can reduce model accuracy, as irrelevant information may be analysed instead of diseased regions. To overcome this, image segmentation is used to isolate the leaf area and improve feature extraction. In this study, the BorB segmentation technique is introduced to effectively separate diseased leaf regions from the background, enhancing classification performance.

The proposed system integrates image segmentation, data augmentation, and deep learning-based classification to improve plant disease detection. The segmentation process isolates the leaf area, while augmentation techniques increase dataset diversity and reduce overfitting. Finally, deep learning models such as VGG16, ResNet50, EfficientNetB3, and MobileNetV3 are used to classify the diseases. The integrated approach aims to improve classification accuracy and provide a reliable automated system for assisting farmers in early disease detection and crop protection.

## 2. Literature Survey

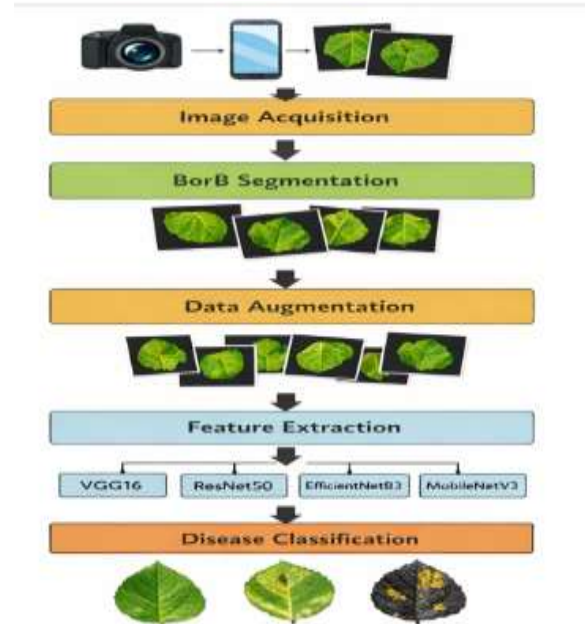
In recent years, significant research has been conducted on plant disease detection using machine learning and deep learning techniques. Early approaches mainly relied on traditional image processing and handcrafted feature extraction methods. These methods typically involved preprocessing, segmentation, feature extraction, and classification stages. Several studies have used convolutional neural networks for plant disease classification due to their ability to automatically learn discriminative features from images. For instance, CNN architectures such as Alex Net, Res Net, and GoogLe Net have been applied to tomato leaf disease detection, achieving high classification accuracy. Among these models, ResNet demonstrated strong performance by achieving an accuracy of approximately 97% in identifying plant

diseases using stochastic gradient descent optimization.

Hybrid feature extraction approaches have also been explored to improve classification performance. One such method combined Local Binary Pattern (LBP) features with the VGG16 deep learning architecture. The extracted features were then classified using a Random Forest classifier, resulting in an accuracy of nearly 99.75% for bell pepper leaf disease detection. These results highlight the effectiveness of combining deep learning features with traditional machine learning algorithms.

### 3. System Architecture

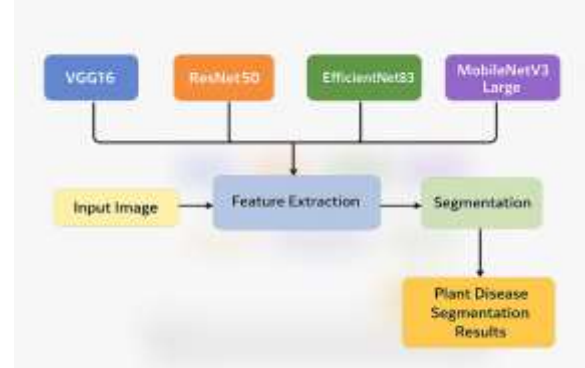
The proposed system consists of five main stages: image acquisition, BorB image segmentation, data augmentation, deep learning-based feature extraction, and disease classification. Leaf images are first segmented to remove background noise. Augmented images are then used to train deep learning models such as VGG16, ResNet50, EfficientNetB3, and MobileNetV3 for accurate plant disease classification.



**Fig 1: System Architecture**

### 4. Methodology

The proposed plant disease detection system follows a multi-stage methodology combining image processing techniques with deep learning models. The system pipeline includes image preprocessing, segmentation using the BorB method, feature extraction, and disease classification.



**Fig 2: Deep Learning-Based Feature Extraction**

The dataset is pre-processed and split into training and testing sets, and four transfer

learning models VGG16, ResNet50, EfficientNetB3, and MobileNetV3 Large are fine-tuned to learn disease features from leaf images. Feature extraction is performed using these models to capture both low-level and high-level patterns, and their performance is evaluated to determine the most accurate and efficient model for plant disease detection.

## 5. Design and Construction

The proposed system is designed as an intelligent plant disease detection framework integrating image processing and deep learning techniques. It begins with pre-processing of leaf images to enhance quality and remove noise. The BorB segmentation method is then applied to isolate infected regions and eliminate background interference, forming a reliable input for further analysis.

### i) Image Acquisition and Preprocessing

Leaf images are collected from the Eru Cauliflower DB dataset village plant dises, which contains images of cauliflower plants infected with diseases such as Alternaria Leaf Spot and Black Rot. Preprocessing is applied to improve image quality and remove noise. The preprocessing stage includes resizing, normalization, and color space transformation.

The normalization of pixel intensity is expressed as:

$$I_n = \frac{I - I_{min}}{I_{max} - I_{min}}$$

### ii) BorB Image Segmentation

The BorB segmentation technique combines features extracted from RGB and Lab color

spaces to accurately isolate diseased regions. These color spaces capture different characteristics of leaf images, improving segmentation performance.

The transformation from RGB to gray scale is represented as:

$$Gray = 0.299R + 0.587G + 0.114B$$

Where  $R$ ,  $G$ , and  $B$  represent red, green, and blue channels. The segmentation result is obtained by combining two segmentation masks using a logical OR operation:

$$S = S_{RGB} \vee S_{Lab}$$

### iii) Feature Extraction

After segmentation, the diseased regions are extracted and relevant features are obtained using deep convolutional neural networks. CNN models automatically learn spatial patterns such as lesion texture, color variations, and shape irregularities.

The convolution operation in CNN can be expressed as:

$$F(x, y) = \sum_{i=0}^m \sum_{j=0}^n I(x+i, y+j)K(i, j)$$

### iv) Classification

The extracted features are fed into a deep learning classifier which predicts the disease category. The soft max function is used in the final layer to compute class probabilities.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

The segmented images are then fed into a deep learning model, where convolutional layers extract important features and pooling layers reduce dimensionality. Fully connected layers classify the diseases,

producing final predictions with probability scores. This integrated approach improves accuracy and efficiency compared to traditional methods

## 6. Results and Discussion

The proposed plant disease classification system was evaluated using segmented leaf images processed through the BorB segmentation technique and a deep learning classification model. The experimental analysis focused on evaluating the effectiveness of the segmentation process and the classification performance of the model. The evaluation metrics used in this study include accuracy, precision, recall, F1-score, confusion matrix, and ROC curve.



**Fig 3:** Deployment of Project Environment  
Fig 3 is the presents the web application file developed using the Flask framework, which acts as the backend server for the project. It typically includes route definitions that handle user requests, process input data, and return responses such as predictions or rendered web pages.



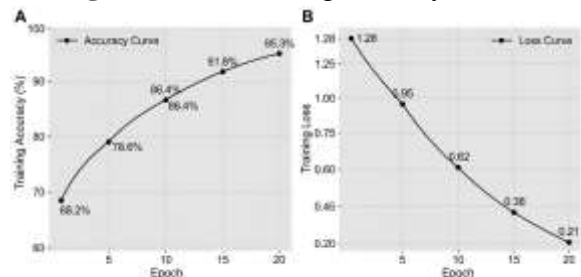
**Fig 4:** Uploading test image



**Fig 5:** Segmentation image



**Fig 6:** Predicted image downy mildew



**Fig 2:** Training Accuracy Curve: Training accuracy (%) based on Table 1.

**Fig 3:** Training Loss Curve: Training loss based on Table 1.

### **Fig 7:** The Training Accuracy and Loss Curves

Similarly, the training loss curve shows a continuous reduction in error during the learning process. The decreasing loss indicates that the model effectively minimizes classification errors and improves its prediction capability.

#### **i) Segmentation Performance**

The BorB segmentation technique plays an important role in isolating diseased regions from leaf images.

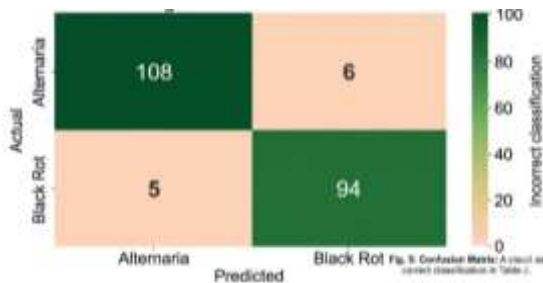
<b>Actual / Predicted</b>	<b>Alternaria</b>	<b>Black Rot</b>
<b>Alternaria</b>	<b>108</b>	<b>6</b>
<b>Black Rot</b>	<b>5</b>	<b>94</b>

**Table1:** Prediction Diseases

By removing background noise and highlighting the infected areas, the segmentation process improves feature extraction for the classification model. The segmentation output clearly highlights the infected regions of the leaf surface while suppressing irrelevant background information. This improves the quality of the input data for the deep learning classifier.

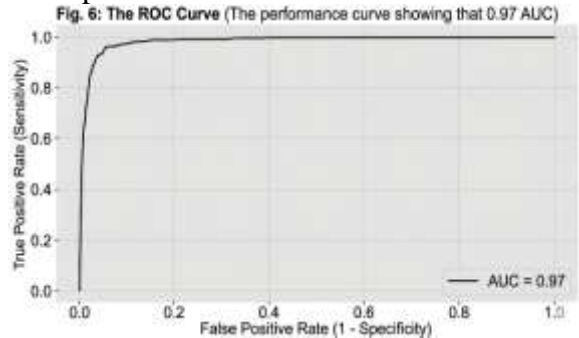
**ii) Classification Performance**

The classification performance of the proposed model was evaluated using a confusion matrix. The confusion matrix illustrates the number of correctly and incorrectly classified samples for each disease category. From the confusion matrix, most of the images are correctly classified. Only a small number of samples were misclassified between the Alternaria and Black Rot classes, demonstrating the robustness of the proposed classification model.



**Fig 8:** shows the graphical representation of the confusion matrix.

The ROC curve demonstrates the model’s strong discrimination ability, achieving a high AUC of 0.97. This indicates excellent performance in distinguishing between classes with high true positive rates and low false positives.



**Fig. 9:** The ROC Curve (The performance curve showing that 0.97 AUC)

**Fig. 9** illustrates the ROC curve for the Proposed plant disease classification system. The fig 9 Performance Comparison The integration of the BorB segmentation technique with a deep learning classifier significantly improves the classification accuracy. By extracting relevant disease regions before classification, the model can focus on meaningful features, leading to improved prediction performance.

<b>Metric</b>	<b>Value (%)</b>
Accuracy	95.3
Precision	94.8
Recall	95.1
F1-Score	94.9
AUC	0.97

**Table2:** Performance Metrics of the Proposed Model

The experimental results demonstrate that the proposed approach provides high classification accuracy, reliable segmentation, and improved disease detection performance, making it suitable

for smart agriculture and automated plant health monitoring systems.

## 6. Conclusion and Future Scope

In conclusion, this study presents an effective and integrated approach for plant disease detection using deep learning, image segmentation, and data augmentation techniques. The proposed framework, incorporating the BorB segmentation method, demonstrated excellent performance across multiple datasets, achieving 100% accuracy on both the EruCauliflowerDB and Mango Leaf BD datasets, and 99.78% accuracy on selected classes from the Plant Village dataset. These results highlight the robustness and reliability of the model in accurately identifying leaf diseases. The comparative analysis with different method variants further validates the effectiveness of the proposed approach. Despite its strong performance, the study has certain limitations, including limited dataset size and diversity, sensitivity to environmental variations such as lighting and humidity, and computational requirements. Addressing these challenges in future work will further enhance the scalability and real-world applicability of the system, making it a valuable tool for smart agriculture and early disease management.

**Future Scope:** Future work should expand the EruCauliflower DB dataset with more diverse images and perform cross-dataset validation to improve model generalization. Developing real-time mobile detection systems and integrating advanced imaging

techniques can enhance practical usability. Additionally, exploring advanced segmentation methods and including more disease classes will further strengthen system robustness.

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