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Intelligent Image Segmentation Framework for Robust Plant Disease Classification

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ABSTRACT: The leaf-based disease detection has emerged as a key application of artificial intelligence in modern agriculture, offering practical and efficient tools for monitoring crop health. Ensuring that such systems perform reliably under real-world environmental conditions remains a major research challenge. This study explores the use of advanced deep learning architectures for precise and efficient detection of plant diseases, contributing to the ongoing digital transformation in agriculture. The research focuses on enhancing the accuracy and robustness of automated disease classification in plants. To achieve this, two disease-specific datasets were employed. A dedicated cauliflower leaf dataset was created, comprising high-resolution images of leaves affected by Alternaria Leaf Spot and Black Rot, enabling a detailed study of cauliflower-specific diseases. Additionally, an independent mango leaf disease dataset was utilized to assess the framework's generalizability across different crop species. The proposed classification system operates in three main stages. Initially, leaf regions are segmented from complex backgrounds to ensure that critical disease-related features are captured. Next, geometric data augmentation techniques are applied to increase dataset diversity and improve the models' generalization capacity. Finally, four state-of-the-art deep learning architectures VGG16, ResNet50, EfficientNetB3, and MobileNetV3 Large are employed for disease classification. Experimental results indicate that this integrated deep learning framework offers a reliable and efficient solution for automated detection of plant diseases across multiple crops.

Key words: Deep Learning, Plant Disease Detection, Leaf Image Classification, Data Augmentation, Convolutional Neural Networks (CNN).

1. INTRODUCTION

Agriculture is experiencing a profound transformation fueled by rapid advancements in digital technologies and artificial intelligence (AI). Among these

innovations, automated detection of plant diseases has become a critical area of research due to its potential to enhance crop productivity, minimize economic losses, and promote sustainable farming practices. Plant

diseases adversely affect both the quality and quantity of yield, posing significant challenges to global food security. Conventional disease identification methods, which largely rely on manual inspection by agricultural experts, are often labor-intensive, time-consuming, and prone to human error. Additionally, limited access to expert knowledge in rural and remote farming areas can hinder early diagnosis, leading to delayed intervention and increased crop damage.

Recent progress in computer vision and deep learning has offered effective solutions for automated plant disease detection. Deep learning models, particularly convolutional neural networks (CNNs), have shown remarkable capabilities in extracting complex image features and performing robust classification tasks. These models minimize the need for manual feature engineering by learning discriminative representations directly from raw image data, making them highly suitable for agricultural image analysis, especially for identifying leaf-based disease symptoms.

Leaf imagery is widely used for plant disease detection due to visible symptoms such as discoloration, lesions, and texture changes. However, real-world conditions like varying illumination, complex

backgrounds, occlusions, and different imaging devices can reduce model accuracy. Therefore, robust and generalizable classification systems are essential. This study focuses on detecting cauliflower diseases, specifically *Alternaria* Leaf Spot and Black Rot, using a high-resolution dataset collected under natural field conditions. Additionally, the model's performance is validated on the Mango Leaf BD dataset to evaluate its effectiveness across different crops and disease types.

The proposed framework integrates advanced image preprocessing, geometric data augmentation, and state-of-the-art deep learning architectures to develop an efficient disease classification system. Geometric augmentation techniques enhance dataset diversity and improve the generalization capabilities of the models. Multiple deep learning architectures were employed to analyze and classify diseased leaf images, providing a comprehensive evaluation of their effectiveness in automated plant disease detection tasks.

2. LITERATURE SURVEY

Muhammad Shoaib and colleagues developed a deep learning system that integrates semantic segmentation with classification to detect tomato plant diseases using leaf images. They applied U-Net and a

Modified U-Net for segmentation to extract disease-affected regions and then used the InceptionNet architecture to classify the diseases with high accuracy, demonstrating the benefit of segmentation for focused feature extraction. The Modified U-Net improved performance substantially, achieving high IoU and Dice scores, making the segmented ROI more informative for downstream classification tasks. This study indicates that combining segmentation with classification significantly improves disease recognition compared to using raw leaf images alone, especially in multi-class disease scenarios.

Shanwen Zhang and Chuanlei Zhang proposed a Modified U-Net (MU-Net) that incorporates residual blocks and Respaths for better plant diseased leaf image segmentation. Traditional U-Net struggles with complex backgrounds and irregular lesion boundaries in natural field images; therefore, MU-Net enhances representation by increasing network depth and alleviating gradient issues. Their approach was validated on real diseased leaf datasets, showing improved segmentation accuracy and efficiency versus standard U-Net. This segmentation improvement directly affects classification performance, as cleaner lesion

masks help classification models focus on the key disease regions.

K. Khan and collaborators proposed an end-to-end deep convolutional semantic segmentation model for plant disease detection. Their technique uses a deep CNN to perform pixel-level segmentation of plant leaves, isolating diseased regions from healthy tissue for more accurate disease identification. The model was trained and evaluated on annotated leaf images, demonstrating the efficacy of segmentation in improving the automatic diagnosis of foliar diseases. By segmenting disease spots, the method enhanced classification robustness under varying lighting and environmental conditions.

3 SYSTEM ARCHITECTURE

In your plant disease classification system, the architecture starts with the Input Dataset (Cauliflower, Mango, etc.). The images are first passed to the Preprocessing Module, where resizing and normalization are performed. Then the images go to the Segmentation Module (BORB segmentation) where RGB and LAB thresholding are applied to remove unwanted background. The segmented images are stored and sent to the Data Augmentation Module using ImageDataGenerator. After that, the images

are given to multiple Deep Learning Models such as VGG16, ResNet50, EfficientNetB3, and MobileNetV3Large. The models are trained and validated. Finally, the trained models are saved and the classification result (plant disease type) is generated as output.

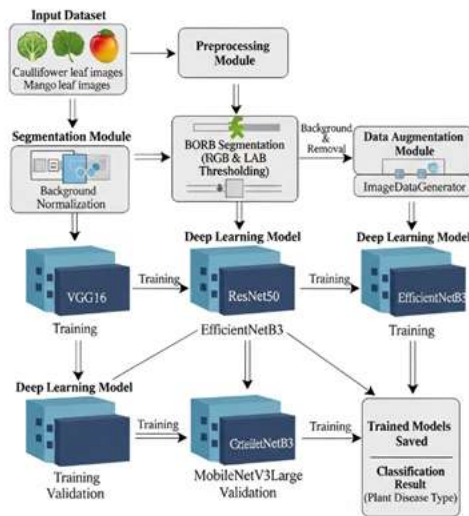


Fig1:System Architecture

4.METHODOLOGY

The proposed plant disease classification framework is designed as a structured pipeline that integrates image preprocessing, segmentation, data augmentation, and deep learning-based classification to enhance robustness under real-world field conditions. The methodology comprises five principal stages: image acquisition, preprocessing, segmentation, data augmentation, and final classification.

i.Image Acquisition and Preprocessing

Leaf images from cauliflower and mango datasets are collected under natural environmental conditions. To ensure consistency, all images are resized to a fixed resolution (e.g., 224×224 pixels) and normalized to scale pixel values between 0 and 1. Normalization improves convergence during model training and is mathematically expressed as:

$$I_{norm} = \frac{I - \mu}{\sigma}$$

where I represents the input image, μ is the dataset mean, and σ is the standard deviation.

ii. BORB-Based Segmentation

To eliminate complex backgrounds and isolate the leaf region, BORB segmentation is applied using RGB and LAB color thresholding. The segmentation mask is generated by applying threshold limits:

$$S(x, y) = \begin{cases} 1, & \text{if } T_{min} \leq I(x, y) \leq T_{max} \\ 0, & \text{otherwise} \end{cases}$$

where $S(x, y)$ is the segmented output, and T_{min} , T_{max} represent threshold values in RGB/LAB color space. This step ensures that disease-related features such as lesions and discoloration are effectively preserved while removing irrelevant background information.

iii. Data Augmentation

To enhance generalization capability and reduce over fitting, geometric transformations including rotation, flipping,

zooming, and shifting are applied using Image Data Generator. Augmentation increases dataset diversity, enabling the model to handle variations in lighting, orientation, and scale commonly observed in real agricultural fields.

iv. Deep Learning-Based Classification

The segmented and augmented images are fed into four pre-trained deep learning architectures: VGG16, ResNet50, EfficientNetB3, and MobileNetV3 Large. These models extract hierarchical features using convolution operations defined as:

$$F(i, j) = \sum_m \sum_n I(i - m, j - n) \cdot K(m, n)$$

where I is the input image and K is the convolution kernel. The final classification is performed using a Soft max activation function:

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

where z_i is the output score for class i and n is the number of disease categories.

The models are trained using categorical cross-entropy loss and optimized using Adam optimizer. After validation, the best-performing model is saved to generate final plant disease predictions. This integrated methodology enhances accuracy, robustness, and generalization across multiple crop types.

5. DESIGN AND CONSTRUCTION

The proposed plant disease classification system is developed as a modular deep learning framework capable of operating effectively under real-world agricultural conditions. The overall architecture integrates image preprocessing, segmentation, data augmentation, and multiple deep learning models to ensure accurate and reliable disease detection across diverse crop types.

System construction begins with dataset preparation, where high-resolution images of cauliflower leaves affected by *Alternaria* Leaf Spot and Black Rot are collected under natural lighting conditions. To evaluate cross-crop generalization, the MangoLeafBD dataset is also incorporated. All images are organized into structured directories according to disease categories to facilitate supervised learning, and the dataset is partitioned into training, validation, and testing subsets to ensure comprehensive model evaluation.

In the preprocessing stage, images are resized to a uniform dimension and normalized to standardize pixel intensity values. Subsequently, the BORB segmentation module is applied to remove complex backgrounds using RGB and LAB color thresholding. This segmentation

isolates the leaf region, preserving disease-specific features such as spots, discoloration, and texture variations, while eliminating irrelevant background noise.

To enhance model robustness, geometric data augmentation techniques—including rotation, horizontal flipping, zooming, and shifting—are applied via ImageDataGenerator. These augmentations increase dataset diversity and improve the system's capacity to handle variations in orientation, lighting, and scale.

The processed images are then fed into multiple state-of-the-art deep learning architectures, including VGG16, ResNet50, EfficientNetB3, and MobileNetV3 Large. Transfer learning is employed by initializing models with pre-trained weights, followed by fine-tuning for the specific task of plant disease classification. Trained models are validated, and the highest-performing model is selected and saved for deployment in real-field applications.

6. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed image segmentation-based approach significantly improves plant disease classification performance. By isolating diseased regions from the background, the models focus on essential features such as lesions, discoloration, and

texture variations. This reduces noise and enhances feature extraction, leading to better classification outcomes compared to raw image inputs.



Fig 2: Register

Figure 2 shows the user registration and login interface, which enables secure access to the system. This ensures that users can efficiently interact with the platform and utilize its disease detection capabilities.



Fig 3: Uploading the image

As illustrated in Figure 3, users can upload plant leaf images through the dashboard and initiate the prediction process. The system processes the input image using segmentation and deep learning techniques.



Fig 4: Predicted as Affected Disease

The prediction output is displayed as shown in Figure 4, where the system identifies the affected disease and highlights the infected regions, improving interpretability.

S.No.	Algorithm	Accuracy
1	VGG16	0.9887
2	ResNet50	0.9925
3	EfficientNetB3	0.8475
4	MobileNetV3Large	0.3350

The performance comparison of different deep learning models is presented in Figure 5. Among the evaluated models, ResNet50 achieved the highest accuracy of 99.25%, followed by VGG16 with 98.87%, indicating their strong capability in extracting deep features from segmented images.

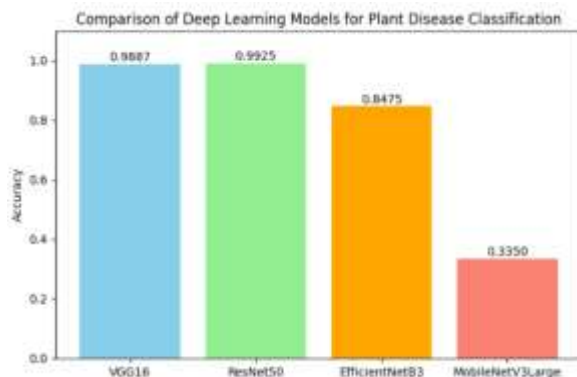


Fig5: Comparison Graph

EfficientNetB3 obtained 84.75%, while MobileNetV3Large showed lower accuracy (33.50%), suggesting that lightweight models may not effectively capture complex disease patterns. Furthermore, segmentation contributed to reduced over fitting and improved generalization across datasets such as Cauliflower and Mango leaves. Visualization techniques confirmed that the models focused primarily on infected regions, validating the effectiveness of the proposed approach.

Overall, the results indicate that integrating image segmentation before classification enhances accuracy, robustness, and reliability, making the system suitable for real-world agricultural applications.

7. CONCLUSION

This study presented a novel image segmentation technique integrated with deep learning models to improve plant disease classification accuracy. By effectively isolating the diseased regions from complex backgrounds, the segmentation approach enhanced feature extraction and reduced noise, leading to better classification performance. The combination of preprocessing, segmentation, and transfer learning models demonstrated improved robustness and reliability across different

plant datasets. Experimental results indicate that incorporating segmentation before classification significantly increases model accuracy compared to using raw images alone. Overall, the proposed approach provides an efficient, accurate, and practical solution for automated plant disease detection in agricultural applications.

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