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A Novel Image Segmentation Technique for Improving Plant Disease Classification with Deep Learning Models

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KEYWORDS

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

ABSTRACT

Leaf-based disease detection has become one of the most prominent applications of artificial intelligence in modern agriculture, providing efficient and practical solutions for crop health monitoring. Developing robust systems that can operate effectively under real-field environmental conditions remains a critical research focus. This study investigates the application of deep learning architectures for accurate and efficient plant disease detection within the framework of the ongoing digital transformation of the agricultural sector. Emphasizing the growing role of AI-driven technologies, the research aims to improve the reliability and effectiveness of automated plant disease classification. To support this objective, two disease-specific datasets were utilized. A curated cauliflower leaf dataset containing high-resolution images of plants infected with Alternaria Leaf Spot and Black Rot was developed to enable focused analysis of cauliflower diseases. In addition, an independent mango leaf disease dataset was employed to further evaluate the generalizability and robustness of the proposed framework across different crops. The developed classification system consists of three primary stages. First, leaf regions were isolated from complex backgrounds to ensure that relevant disease-related features were effectively captured. Second, geometric data augmentation techniques were applied to enhance data diversity and strengthen model generalization capability. Finally, four state-of-the-art deep learning architectures VGG16, ResNet50, EfficientNetB3, and MobileNetV3 Large were implemented for disease classification. The experimental findings demonstrate that the proposed integrated deep learning framework provides a reliable and efficient approach for automated plant disease detection across multiple crop types.

I. INTRODUCTION

Agriculture is undergoing a significant transformation driven by rapid advancements in digital technologies and artificial intelligence (AI). Among these innovations, automated plant disease detection has emerged as a critical research area due to its potential to improve crop productivity, reduce economic losses, and support sustainable farming practices. Plant diseases directly affect yield quality and quantity, posing serious challenges to global food security. Traditional disease identification methods, which rely heavily on manual inspection by agricultural experts, are often time-consuming, labor-intensive, and subject to human error. Furthermore, limited access to expert knowledge in rural or remote farming regions makes early diagnosis difficult, leading to delayed treatment and increased crop damage.

Recent developments in computer vision and deep learning have provided promising solutions for automated plant disease detection. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated strong capabilities in extracting complex features from images and performing robust classification tasks. These models reduce the need for manual feature engineering and can learn discriminative representations directly from raw image data. As a result, they have become widely adopted in agricultural image analysis, especially for leaf-based disease identification.

Leaf images are commonly used in plant disease detection because visual symptoms such as discoloration, lesions, and texture changes are typically manifested on leaf surfaces. However, real-world agricultural environments introduce several challenges, including varying lighting conditions, complex backgrounds, occlusions, and differences in image acquisition devices. These factors can negatively influence model performance if not properly addressed. Therefore, developing classification systems that are resilient to environmental variations and capable of generalizing across different crop types remains an important research objective.

In this study, we focus on the detection and classification of diseases affecting cauliflower plants, specifically Alternaria Leaf Spot and Black Rot, which are among the most damaging diseases impacting cauliflower production. A dedicated cauliflower leaf image dataset was constructed using high-resolution images captured under natural conditions to better reflect real agricultural scenarios. To further evaluate the robustness and adaptability of the proposed framework, experiments were also conducted using the independent MangoLeafBD dataset, enabling assessment across different plant species and disease characteristics.

The proposed framework integrates image preprocessing, data augmentation, and advanced deep learning architectures to build an efficient disease classification system. Geometric data augmentation techniques are employed to enhance dataset diversity and improve model generalization. Multiple state-of-the-art deep learning models are utilized to analyze and classify diseased leaf images, allowing a comprehensive evaluation of their performance in agricultural 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.

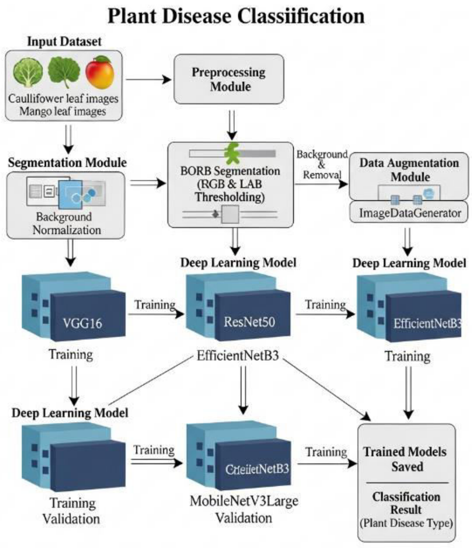

Fig1: System Architecture

4.METHODOLOGY

The proposed plant disease classification framework follows a structured pipeline integrating preprocessing, segmentation, data augmentation, and deep learning-based classification to improve robustness under real-field conditions. The methodology consists of five major stages: image acquisition, preprocessing, segmentation, augmentation, and 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 Irepresents the input image, $\mu$is the dataset mean, and $\sigma$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:

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

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 designed as a modular deep learning framework capable of operating under real-field agricultural conditions. The overall architecture integrates image preprocessing, segmentation, data augmentation, and multiple deep learning models to ensure reliable and accurate disease detection across different crop types.

The construction of the system begins with dataset preparation. High-resolution images of cauliflower leaves infected with Alternaria Leaf Spot and Black Rot are collected under natural lighting conditions. Additionally, the MangoLeafBD dataset is incorporated to evaluate cross-crop generalization. All images are organized into structured directories based on disease categories to facilitate supervised learning. The dataset is divided into training, validation, and testing subsets to ensure proper model evaluation.

The preprocessing module resizes images to a uniform dimension and applies normalization to standardize pixel intensity values. Following preprocessing, the BORB segmentation module is implemented to remove complex backgrounds using RGB and LAB color thresholding. This step isolates the leaf region, ensuring that disease-specific features such as spots, discoloration, and texture variations are preserved while eliminating noise from irrelevant background elements.

To enhance model robustness, geometric data augmentation techniques such as rotation, horizontal flipping, zooming, and shifting are applied using ImageDataGenerator. This increases dataset diversity and improves the system's ability to handle variations in orientation, lighting, and scale.

The segmented and augmented images are then passed to multiple deep learning architectures including VGG16, ResNet50, EfficientNetB3, and MobileNetV3 Large. Transfer learning is employed by initializing models with pre-trained weights and fine-tuning them for plant disease classification. The trained models are validated, and the best-performing model is saved for deployment.

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.

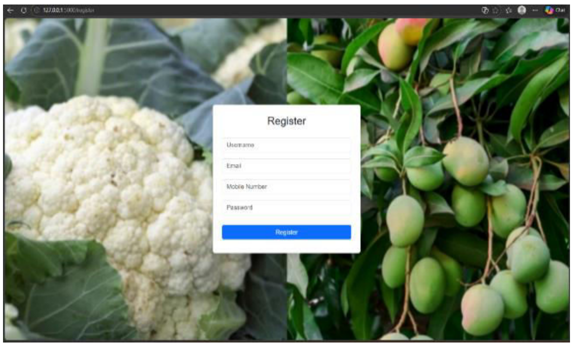

Fig 2: Register

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.

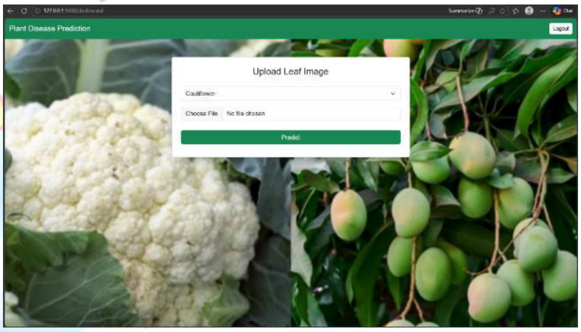

Fig 3: Uploading the image

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.

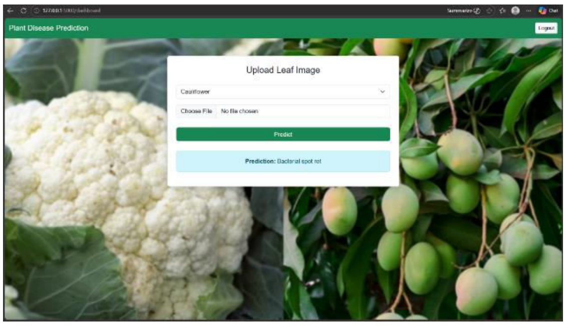

Fig 4: Predicted as Affected Disease

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.

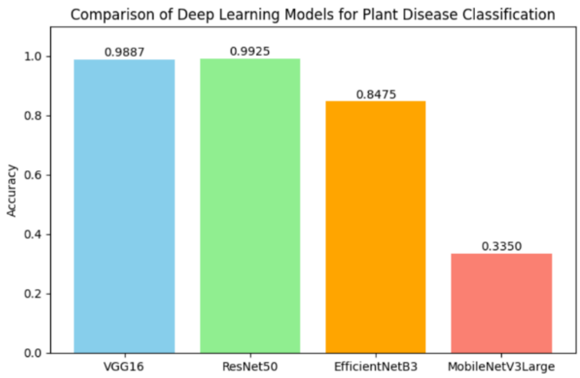

Fig5: Comparison Graph

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.

FUTURE SCOPE

The future scope of this work includes integrating advanced transformer-based models like Vision Transformers (ViT) to improve feature extraction and capture global patterns in plant disease detection. Hybrid CNN–Transformer approaches and self-supervised learning can further enhance accuracy while reducing dependence on labeled data. Developing lightweight, edge-deployable models will enable real-time disease detection using mobile or IoT devices. Expanding datasets and incorporating multimodal data such as weather, soil, and hyperspectral inputs can improve robustness and support precision agriculture.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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