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IMPROVED CONVOLUTIONAL NETWORK WITH TRANSFER LEARNING AND TEXTURE FEATURE EXTRACTOR FOR PLANT DISEASE DETECTION

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ABSTRACT

Plant diseases pose a significant threat to agriculture worldwide, impacting both productivity and food security. Effective disease management relies on early detection and accurate diagnosis. Traditional methods, which depend on visual inspection, are often slow and subjective. However, recent advancements in computer vision and machine learning offer promising alternatives. This paper presents an enhanced framework for plant disease segmentation that combines preprocessing with segmentation techniques. The initial preprocessing stage uses median filtering to refine the data, while the segmentation stage employs the Adaptive Pixel Integration in Joint Segmentation (APIJS) method. This approach, a variant of DJS, is designed to accurately isolate disease-affected regions in plant images. By improving the precision and effectiveness of plant disease segmentation, this framework contributes to advancing sustainable agriculture and strengthening global food security.

Keywords: *Plant Disease Detection, Median Filter, APIJS, Global Food Security.*

Introduction

In recent years, automated plant disease detection has emerged as a significant challenge in precision agriculture. Advances in disease detection technology have revolutionized early diagnosis and accurate prediction of plant diseases [12]. These technologies enable farmers to consistently monitor plant health and growth, even amidst varying environmental conditions. Despite these advancements, the high degree of similarity among different disease groups and the variability within the same disease class continue to present challenges. Early identification and prediction of plant diseases are crucial for effective disease management and control [13]. Plants are susceptible to a range of factors, including weeds, insects, bacteria, and fluctuating climate conditions. Timely detection is essential to mitigate damage and ensure optimal crop yields, particularly for common issues such as green leaf spots, scabs, and mosaic viruses.

The field of plant disease detection has seen rapid advancements thanks to the application of machine learning (ML) and deep learning (DL) techniques, which are yielding promising results. Among these, deep learning [20][21] has proven particularly effective in image recognition, as it automatically extracts features from images rather than relying on manually selected ones.

This makes deep learning (DL) a powerful tool for automating the detection of disease-related features in plants [14]. However, several challenges persist. One major issue is the difficulty in obtaining

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real-world field datasets that are suitable for training DL models [15]. Plant diseases are often randomly distributed across leaves, stems, and roots, and they vary in texture, size, and shape, complicating detection tasks. Additional complexities arise from environmental factors such as wind-blown haze, overlapping leaves, intricate backgrounds, and varying angles of view.Many studies have proposed DL-based methods for detecting and identifying plant diseases [16][19]. Despite this, challenges remain, such as the need to compile extensive datasets that cover all types of diseases across different leaf shapes. Additionally, the rapid spread of some diseases makes it challenging to detect them in time on leaves. The performance of DL [18] systems is directly impacted by this lack of data. These systems find it difficult to generalize the patterns required for accurate plant disease identification when they lack access to large datasets. As a result, this research suggests a unique method for dataset image segmentation.

This work contributes the following:

- Utilizing median filtering to preprocess the input image, enhancing it for subsequent analysis.
- Introducing the APIJS approach in the segmentation phase to reduce excessive noise and prevent over-segmentation in the preprocessed image.

The remainder of the document is structured as follows: Section 2 contains an overview of the literature on the works currently in publication. Section 3 explains the suggested methodology. Section 4 presents the results and discussion and Section 5 provides a summary of the suggested model.

Literature Review

In 2024, Sasikala Vallabhajosyula *et al.* [1] A model was proposed to assist in the early detection of leaf diseases, featuring a novel hierarchical residual vision transformer. This model integrates enhanced features from ResNet9 and Vision Transformer models, aiming to extract more discriminative and meaningful details while reducing computational demands and the number of trainable parameters. The effectiveness of the model was evaluated using three datasets: the Local Crop dataset, Plant Village dataset, and Extended Plant Village Dataset. Training involved optimized parameters from the Improved Vision Transformer and leveraged ResNet9 for feature classification.

In 2024, Imane Bouacida *et al*. [2] A novel deep learning-based system was introduced to recognize both diseased and healthy leaves across various crops, even if the system had not been specifically trained on those crops. Instead of merely classifying a leaf as diseased or healthy, this method identifies specific regions affected by the disease and quantifies the percentage of the leaf that is diseased. Designed for efficient analysis of small areas without performance degradation, the system was validated by training and testing on the PlantVillage dataset, renowned for its comprehensive coverage of a wide range of plant diseases.

In 2024, K. Mahadevan *et al*. [3] A novel approach for detecting rice plant leaf diseases was introduced, incorporating DSGAN with Improved Artificial Plant Optimization. The method starts by inputting images of healthy and diseased leaves from a curated dataset. The ITNN technique is then used to enhance image quality. Next, the SMNS algorithm performs segmentation to identify regions of interest based on improved color saturation in the images. Finally, disease detection is carried out using the proposed SMLAF method alongside DSGAN, leveraging the extracted features for precise classification.

Table 1: Features and Challenges of Extant Works

Authors	Methodology	Features	Challenges
Sasikala Vallabhajosyula, et al. [1]	Improved Vision Transformer and ResNet9 models	Achieved consistent results with the Adam optimizer; highest accuracy with the SGD optimizer.	Future work will focus on developing a compact DNN to address real-time data processing challenges.
Imane Bouacida, et al. [2]	Deep Learning (DL)	Shows enhanced versatility and resilience across a wide range of crops and diseases.	Future research should aim to improve the model's efficiency and effectiveness in practical applications.
K. Mahadevan, et al. [3]	DSGAN2	Demonstrated faster processing times compared to most existing models, with a processing time of 98 milliseconds.	To improve future models, researchers should expand training data to include more rice plant species and diseases.

Problem Statement

The fast and accurate plant disease identification is essential for food security and sustainable agriculture. Automated systems capable of analyzing images of plant parts, particularly leaves, to identify and classify diseases play a pivotal role in modern agriculture. There are numerous challenges associated with accurately identifying and classifying plant diseases using image-based methods.

An Overview of Plant Disease Detection Using Transfer Learning

The framework is organized into two distinct stages: **preprocessing** and **segmentation**, as illustrated in Figure 1. Initially, preprocessing prepares raw data for further analysis, employing median filtering to ensure data quality and consistency. The segmentation stage then isolates regions of interest using the APIJS approach, which is a variant of DJS that adjusts pixel values during the joining phase. This method focuses on areas within plant images that may be affected by diseases. After segmentation, feature extraction identifies and quantifies key characteristics from these regions, which is essential for accurate disease classification.

Furthermore, this predictive capability offers valuable insights for agricultural decision-making, allowing farmers to implement targeted treatments and interventions quickly. As agricultural challenges increase with rising global demand, innovative frameworks such as APIJS mark significant progress in the segmentation process, helping to protect crop health and secure food supplies for future generations.

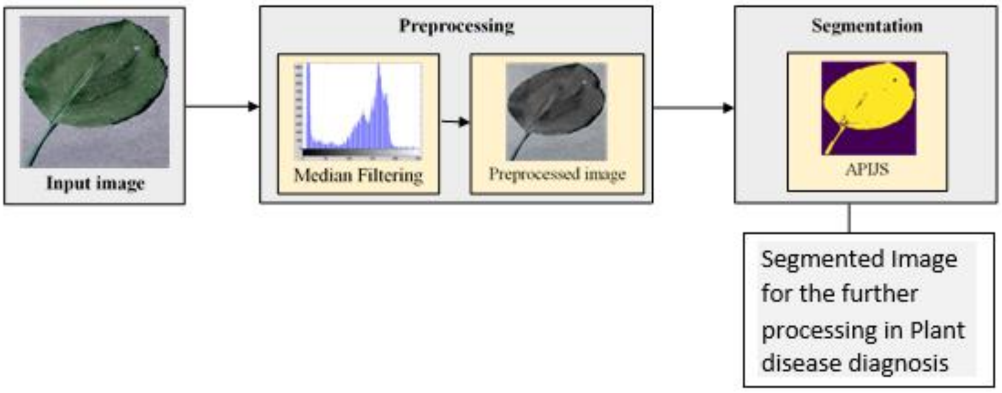

Figure: Architecture of Proposed Model

Let the input plant leaf image for predicting the plant disease. Plant leaf images captured under varying conditions may contain noise such as background clutter, lighting variations, or artifacts from the imaging process. Preprocessing techniques like noise reduction filters (e.g., median filtering) help to clean up these images, ensuring that the features relevant to disease detection are clear and distinct. The description of median filtering is as follows:

Segmentation

In image processing, segmentation is the process of diving image up into discrete areas or segments according to standards such as motion, texture, color, intensity, or other factors. This process aims to simplify the image representation and make it more manageable for analysis. In this work, an adapted version of DJS method known as APIJS is employed and the process of APIJS approach is discussed in the following.

APIJS Approach for Image Segmentation

In this step, the pre-processed image, undergoes the proposed APIJS method, which is the extension of DJS approach. This method finds the best segments by considering the distance between segmentation points and deep spots in the image, as well as area similarity. The DJS algorithm comprises three primary stages: joining, region fusion, and segmentation point generation.

Table 2: Distribution of Classes and Total Number of Images in the Dataset

Classes	Total Number of Images
Apple_Blackrot	621
Apple_Healthy	1645
Grape_Blackrot	1180
Grape_Esca_Black_measles	1383

Performance Analysis

Sample and pre-processed images that underwent median filtering as part of the plant disease detection system are shown in Figures. These images pertain to Apple crops (Healthy, Black Rot, and Scab) and Grape crops (Blackrot, Esca, Healthy, and Leaf Blight).

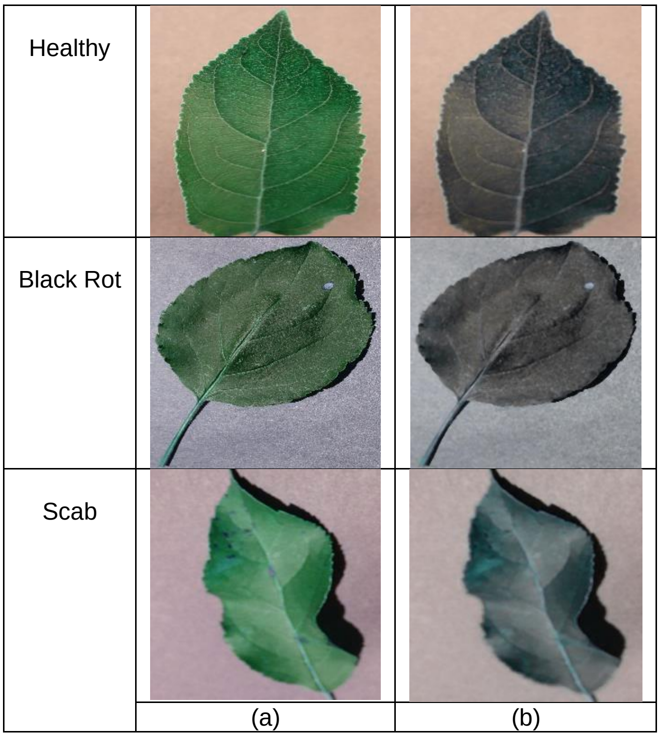

Figure: Images for plant disease detection using Apple Class a) Original Images and b) Median Filtering using Pre-processed image

Segmentation Analysis on Apple and Grape Class

Figure show the original images alongside segmented images generated by various segmentation models used in plant disease prediction, including BIRCH, Conventional DJS, FCM, U-Net, K-means, and APIJS. These figures showcase how each segmentation method processes and identifies diseased regions within the plant images. Notably, APIJS stands out by producing superior outcomes contrasted to existing segmentation models, demonstrating its enhanced ability in precisely delineating and highlighting diseased areas.

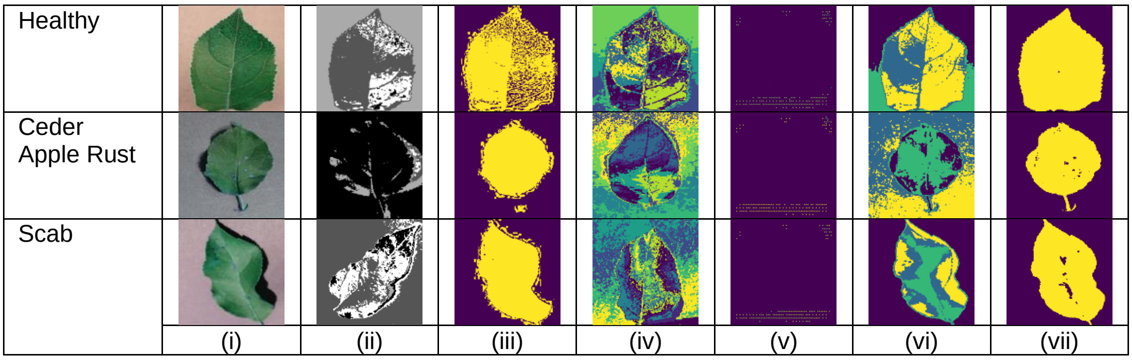

Figure: Images for plant disease prediction using Apple Class i) Original Image ii) BIRCH iii) Conventional DJS iv) FCM v) U-Net vi) K-means and vii) APIJS

Conclusion

This paper presents the Transfer Learning-based Plant Disease Detection (TL-PDD) framework. The process begins with preparing and preprocessing raw data using median filtering to ensure consistency and quality. Segmentation then isolates areas of interest using the APIJS approach, a variant of DJS that adjusts pixel values during the Joining phase to highlight potentially diseased regions in plant images. This approach significantly enhances the efficiency and accuracy of plant disease detection systems, contributing to global food security and sustainable agriculture efforts.

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