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Research Paper

A NOVEL IMAGE SEGMENTATION TECHNIQUE FOR IMPROVING PLANT DISEASE CLASSIFICATION WITH DEEP LEARNING MODELS

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Abstract

This study proposes a deep learning-based framework for automated plant leaf disease detection by integrating image segmentation and classification into a unified pipeline. The model is built on a U-Net-based architecture, which performs pixel-level segmentation using an encoder–decoder structure with skip connections to capture both spatial and contextual features. A Kaggle-based leaf disease segmentation dataset with annotated images and masks is used, along with preprocessing techniques such as resizing, normalization, and data augmentation to improve generalization. The training process employs the Adam optimizer with a combination of Binary Cross-Entropy and Dice loss functions to enhance segmentation accuracy. Additionally, a classification module is incorporated to determine whether a leaf is healthy or diseased. Experimental results demonstrate high classification accuracy and effective leaf region segmentation, although fine-grained lesion detection remains limited due to class imbalance and background complexity. Overall, the proposed approach highlights the potential of deep learning techniques in precision agriculture and provides a scalable solution for automated disease detection and crop monitoring.

KEYWORDS:

Image segmentation ,Deep learning,Leaf segmentation,Disease classification,UNet++ precision Agriculture.

I. Introduction

Agriculture plays a vital role in the global economy and is the primary source of livelihood for a large portion of the world's population. However, plant diseases remain a significant challenge, causing substantial reductions in crop yield and quality. Early detection and accurate identification of plant diseases are essential to minimize losses and ensure food security. Traditionally, disease diagnosis is carried out through manual inspection by agricultural experts, which is often time-consuming, subjective, and not easily accessible to farmers in remote areas.

With the rapid advancement of technology, deep learning and computer vision have emerged as powerful tools for automating plant disease detection. These techniques enable systems to analyze images of plant leaves and identify disease patterns with high accuracy. However, one of the key challenges in this domain is the presence of

complex backgrounds, varying lighting conditions, and overlapping features, which can affect the performance of classification models.

To address these challenges, image segmentation plays a crucial role by isolating the leaf region and highlighting diseased areas. By focusing only on the relevant portions of the image, segmentation improves the accuracy and reliability of disease classification. In this project, advanced segmentation models such as UNet++, DeepLabV3, and Swin Transformer are utilized to effectively extract meaningful features from plant leaf images. These models are well-known for their ability to capture both local and global contextual information, making them suitable for handling complex image data.

Agriculture plays a vital role in sustaining the global economy and ensuring food security for a rapidly growing population. However, crop productivity is significantly affected by various biotic stresses, particularly plant leaf diseases, which can lead to substantial yield losses if not detected and treated at an early stage. Traditional methods of disease identification rely heavily on manual inspection by experts, which is time-consuming, labor-intensive, and often prone to human error. Moreover, the increasing scale of agricultural activities makes continuous monitoring impractical using conventional approaches. Therefore, there is a growing need for automated, efficient, and accurate systems for plant disease detection.

II. Literature Survey

Singh.G et al., [1]“Enhanced Leaf Disease Segmentation Using U-Net Architecture for Precision Agriculture,” 2023: This study uses a Leaf Disease Segmentation dataset (7056 images) with U-Net, applying preprocessing, augmentation, and Adam optimizer. It achieved 99.70% training and 98.99% validation accuracy. The model effectively segments diseased regions at pixel level. It is highly relevant as it validates U-Net’s effectiveness and accuracy for precise leaf disease segmentation similar to our approach.

Wang,C.et.al.,[2] “Cucumber Leaf Disease Severity Classification Using DeepLabV3+ and U-Net Fusion,” 2022: This work uses a two-stage DUNet model with cucumber leaf images in complex backgrounds. DeepLabV3+ segments leaves, while U-Net extracts disease spots. It achieved 93.27% segmentation accuracy and 92.85% classification accuracy. This is relevant as it highlights combining segmentation models to improve robustness and severity estimation, useful for our system.

Bhatti,M.et.al.,[3]“CNN and U-Net for Crop and Weed Segmentation,” 2021: Using satellite image datasets with masks, this study applies U-Net with preprocessing and evaluation metrics like IoU and Dice. Results show effective segmentation and importance of dataset size. It relates to our work by demonstrating U-Net’s capability in agricultural segmentation tasks with structured evaluation metrics.

M.S.Chen.et.al.,[4] “Enhanced U-Net CNN for Multi-Class Rice Leaf Disease Segmentation,” 2022: This research uses field-acquired rice leaf datasets with four classes and applies U-Net for segmentation and CNN for classification. It achieved 76.36% accuracy with some overfitting. It is relevant as it combines segmentation and classification, similar to our goal of identifying disease type along with segmented output.

Faturrohman.et.al.,[5] “Lightweight U-Net for Wheat Disease Severity Estimation,” 2023: Using wheat spike images, the model integrates MobileNetV3 and Coordinate Attention for efficient segmentation. It achieved 88.87% MIoU with reduced

parameters. This relates to our idea by showing lightweight models can maintain performance while improving efficiency for real-time applications.

Wang.et.al.,[6] “Modified U-Net for Weed Segmentation in Field Images,” 2020: This study uses augmented weed datasets and a two-stage training approach (pre-training and fine-tuning). It achieved 92.91% IoU and fast segmentation time. It is relevant as it demonstrates handling complex backgrounds and improving segmentation accuracy through augmentation, which is useful for our dataset.

Shi. L.et.al.,[7]“RAM-UNet for Soybean Stem Segmentation,” 2023: Using a custom soybean dataset, this model integrates ResNet50, attention modules, and deformable convolutions, achieving 90.58% mIoU. It shows improved feature extraction in complex scenarios. This is relevant as it highlights advanced U-Net modifications to enhance segmentation accuracy in challenging agricultural images.

Zhu, L., et al., [8]“Efficient U-Net for Potato Disease Segmentation,” 2022: Using 1000 potato leaf images, EfficientUNet-B3 improves MIOU to 83.25% and Dice to 90.86%. Attention mechanisms enhance small lesion detection. It relates to our work by emphasizing efficient architectures for accurate disease segmentation in small and complex regions.

Sunil, G., et al.,[9] “NJ-UNet for Tomato Leaf Segmentation and LAI Estimation,” 2023: This study uses greenhouse tomato datasets and introduces attention-based U-Net with porosity analysis. It achieved strong LAI prediction ($R^2=0.90$). It is relevant as it demonstrates combining segmentation with further analysis, similar to our idea of extracting disease insights from segmented images.

Prakash, N., et al.,[10] “U-Net Autoencoder for Sesame Leaf Disease Detection,” 2022: Using hyperspectral imaging datasets, the model applies anomaly detection via reconstruction error. It achieved >0.8 accuracy in visible spectrum. It relates to our work by showing U-Net’s adaptability to advanced data types for early disease detection.

Zhang, K., et al.,[11] “Dual-Attention U-Net for Grape Disease Segmentation,” 2023: Using grape leaf datasets, this model integrates VGG backbone, ASPP, and attention modules, achieving 94.33% accuracy and 91.09% MIOU. It is relevant as it highlights improvements in boundary detection and segmentation precision using attention mechanisms.

Lee, M., et al.,[12] “CRF-Enhanced U-Net for Weed and Crop Segmentation,” 2021: Using multispectral sunflower datasets, U-Net with CRF achieved 0.883 mean IoU. It improves segmentation using NDVI and NIR inputs. This is relevant as it demonstrates combining spectral data with U-Net to enhance segmentation accuracy in agriculture.

Sahin, H. M., et.al., [13]“DU-Net-L for Alfalfa Image Segmentation,” 2023: Using alfalfa datasets, this model fuses DeepLabV3+ and U-Net with ResNet34 backbone, achieving 99.83% accuracy and 0.94 MIOU. It relates to our work by showing hybrid models outperform standalone architectures in segmentation tasks

Tian,W.,et.al.,[14]“CRUN-Based Leaf Disease Segmentation and Stage Identification,” 2021: Using sugarcane and banana datasets (including Kaggle), this model combines CNN and U-Net with morphological analysis. It effectively segments disease and identifies severity stages. It is relevant as it integrates segmentation with disease stage prediction similar to our project objective.

Chen,D.,et al.,[15]“Hybrid CNN for Plant Leaf Disease Classification,” 2020: Using PlantVillage dataset (10,861 images), this model achieves 94% accuracy using hybrid CNN segmentation. It relates to our work by demonstrating high accuracy in disease classification using deep learning.

Zhou, Y., et al., [16]“SUNet for Coffee Leaf Disease Detection,” 2022: Using JMuBEN datasets, SUNet combines U-Net, SegNet, and Mask R-CNN, improving IoU and F1-score. It relates to our idea by showing hybrid architectures improve detection and segmentation performance.

III. System Analysis

Plant diseases significantly affect agricultural productivity and crop quality. Early and accurate detection is essential to minimize losses and improve yield. Traditional disease detection methods rely on manual inspection, which is time-consuming and error-prone. With advancements in image processing and deep learning, automated detection systems have become feasible. The system must analyze leaf images to identify disease symptoms such as spots, discoloration, and texture changes. It should separate the diseased region from the healthy background for better accuracy. Handling variations in lighting, background, and image quality is a key challenge. Deep learning models can capture complex visual patterns effectively. The system must ensure high accuracy and real-time processing. Scalability is important for large agricultural applications. Overall, an intelligent segmentation-based classification system is required.

Existing System

Existing systems for plant disease detection often use basic image processing techniques. These include thresholding, edge detection, and color-based segmentation. Some systems apply machine learning models like SVM and KNN for classification. However, these approaches rely heavily on manual feature extraction. Deep learning models are used in some cases but without proper segmentation. Many systems analyze the entire image, including irrelevant background information. This reduces classification accuracy. Existing methods are sensitive to lighting and environmental conditions. They often fail to detect early-stage diseases. Real-time implementation is limited. Scalability is also a challenge. Overall, existing systems provide moderate performance but lack precision and robustness.

Disadvantages of Existing System

- Low accuracy due to background noise
- Dependence on manual feature extraction
- Poor performance under varying conditions
- Limited detection of early-stage diseases
- Lack of proper segmentation techniques
- Low scalability and efficiency
- Inconsistent results

Proposed System

The proposed system introduces a novel image segmentation technique integrated with deep learning models. It first preprocesses the input image to enhance quality. Advanced segmentation methods such as U-Net or Mask R-CNN are used to isolate diseased regions. This improves the focus on relevant features. Convolutional Neural Networks (CNNs) are then used for classification. The system can accurately identify

different plant diseases. It reduces the impact of background noise and environmental variations. The model is trained on a large dataset of labeled images. Data augmentation techniques improve robustness. The system provides real-time detection and classification. It can be deployed as a mobile or web application. Overall, it offers a highly accurate and efficient solution.

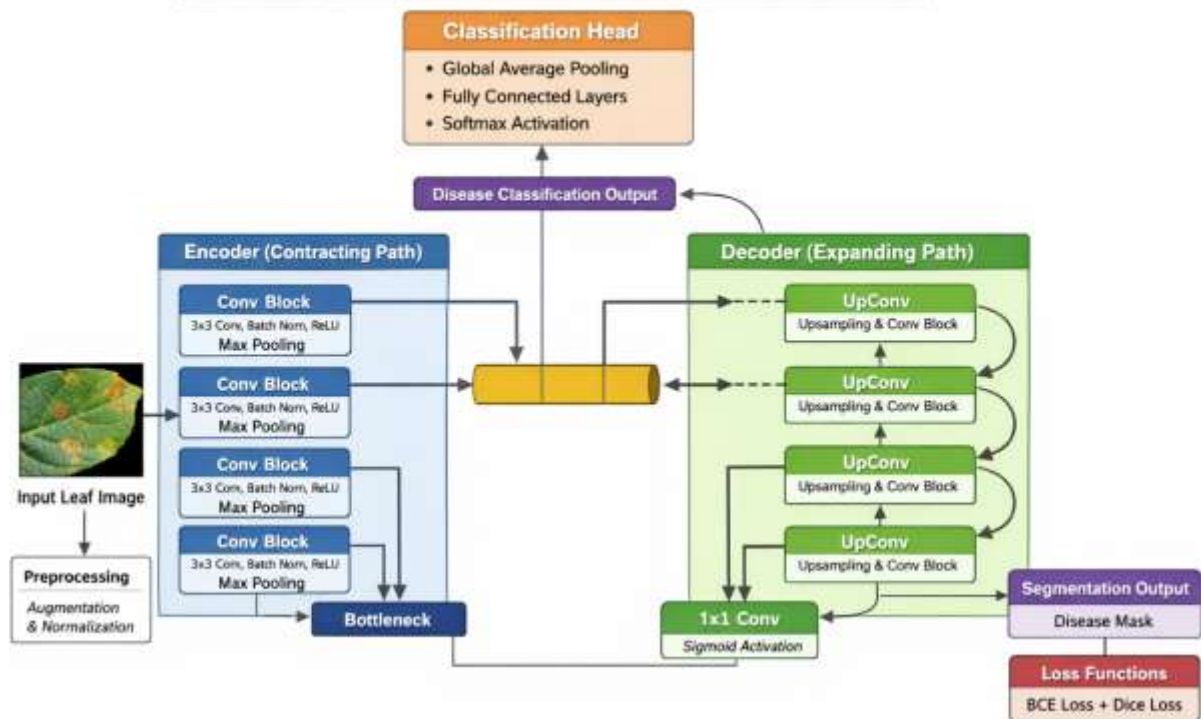
Advantages of Proposed System

- Improved accuracy through segmentation
- Effective removal of background noise
- Automated feature extraction using deep learning
- Better detection of early-stage diseases
- Robust under varying environmental conditions
- Scalable and efficient system
- Real-time detection capability

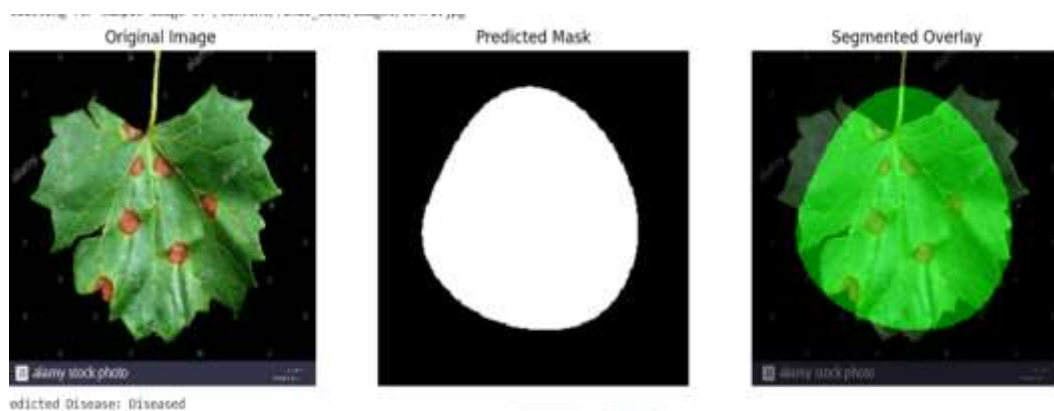
IV. Methodology

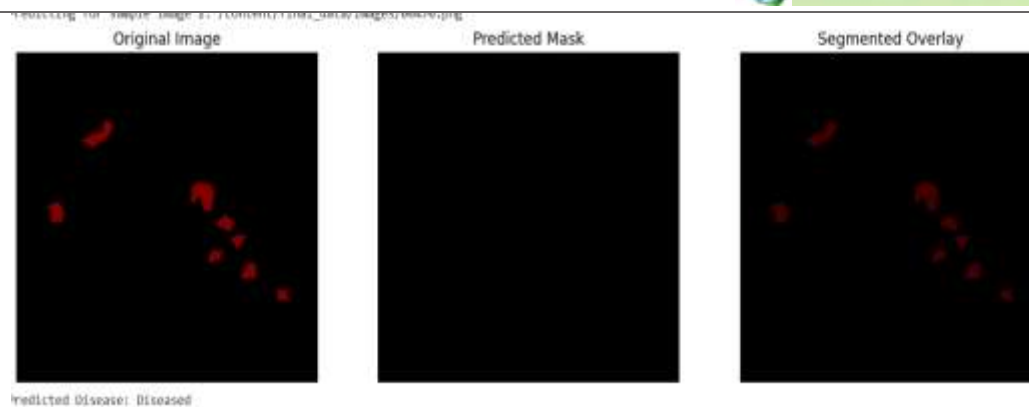
The methodology begins with collecting plant leaf images from datasets or field sources. Data preprocessing is performed to enhance image quality and remove noise. Image segmentation techniques are applied to isolate diseased regions. Advanced models like U-Net are used for precise segmentation. Feature extraction is performed automatically using CNNs. The dataset is divided into training and testing sets. The classification model is trained to identify different diseases. Data augmentation is applied to improve model generalization. Model performance is evaluated using accuracy, precision, recall, and F1-score. Hyperparameter tuning is performed to optimize results. The best model is selected for deployment. The system is integrated into a user-friendly interface.

System Architecture

Proposed Plant Disease Segmentation and Classification Model

The system architecture consists of multiple layers. The image acquisition layer captures plant leaf images. The preprocessing layer enhances image quality. The segmentation layer isolates diseased regions using advanced techniques. The feature extraction layer identifies important patterns. The model layer uses deep learning algorithms for classification. The prediction layer determines the type of disease. The database layer stores images and results. The user interface allows interaction with the system. The feedback layer updates the model with new data. All components are integrated into a unified framework. The system ensures accurate and efficient disease detection. Overall, the architecture supports scalability and real-time processing.

V. Result and Output



VI. Conclusion

The proposed study presents a deep learning-based approach for plant leaf disease detection by integrating U-Net-based segmentation with a classification module. The model demonstrates strong capability in identifying diseased leaves and producing meaningful segmentation outputs, proving its effectiveness for automated agricultural analysis. Although the classification performance is reliable, the segmentation results mainly capture the overall leaf region rather than precise lesion boundaries, indicating the need for further refinement. The application of preprocessing techniques and combined loss functions enhances the model's learning ability and generalization. Despite certain limitations, the framework provides a solid foundation for developing intelligent crop monitoring systems. Future improvements, such as incorporating attention mechanisms, better annotated datasets, and advanced deep learning architectures, can significantly enhance segmentation accuracy. Overall, the model shows promising potential in supporting precision agriculture and reducing manual effort in plant disease detection.

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