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Research Article

Herbal Diseases

Plant Disease Detection Using Image Segmentation

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Abstract: This paper presents a novel approach for detecting plant diseases using image segmentation techniques. The proposed method employs deep learning algorithms to segment images into healthy and infected areas, and then classifies the disease based on the segmented region. The use of image segmentation allows for the automated detection and quantification of diseases in plants, making it a valuable tool for farmers and researchers. Experimental results show that the proposed method achieves high accuracy in detecting various plant diseases, including leaf spot, powdery mildew, and rust. The method's performance was evaluated on a dataset of plant images, demonstrating its effectiveness in real-world applications. The proposed approach has the potential to revolutionize the way plant diseases are detected and managed, improving crop yields and reducing losses due to disease outbreaks.

Keywords: Deep Learning, Image Segmentation, Sematic Segmentation, Transfer Learning, Case Report

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Introduction

Plant diseases are a major threat to global food security, causing significant economic losses and impacting human health. Timely and accurate detection of plant diseases is crucial to prevent their spread and minimize the damage caused to crops. Traditional methods for disease detection are time-consuming and often require expert knowledge, making them impractical for large-scale monitoring. With the increasing availability of imaging technology, computer vision techniques offer a promising solution for automated disease detection in plants.

Image segmentation is a key technique in computer vision that involves dividing an image into meaningful regions. It has been successfully applied in various applications, including medical imaging, autonomous driving, and surveillance. In the context of plant disease detection, image segmentation allows for the identification of healthy and diseased regions in plant images. The use of deep learning algorithms has significantly improved the accuracy of image segmentation, making it a valuable tool for automated disease detection in plants.

This paper proposes a novel approach for plant disease detection using image segmentation techniques. The proposed method employs deep learning algorithms to segment images into healthy and infected areas, enabling the automated detection and quantification of diseases in plants. The method's performance was evaluated on a dataset of plant images, demonstrating its effectiveness in detecting various plant diseases, including leaf spot, powdery mildew, and rust.

The organization of the paper is as follows: In Section 2, the material and methods are explained. Section 3 explains the result and discussion about the current study. In the last section the conclusion of the current study is mentioned.

Materials and Methods

Dataset

The dataset used in this study is the PlantDoc dataset [1], a collection of images of diseased and healthy plant leaves for various plant species, collected under natural lighting conditions. The dataset is intended for use in developing and Evaluating computer vision algorithms for automatic plant disease diagnosis.

For our study, we randomly selected 500 images from the PlantDoc [1] dataset, consisting of 500 images of diseased plant leaves. The diseased plant leaves in our sample included various types of plant diseases, such as bacterial blight, bacterial spot, gray mold, powdery mildew, and rust, among others.

To train our deep learning model for plant disease detection, we generated segmentation masks for each image in our sample. The segmentation masks were created using the open-source annotation tool VGG Image Annotator (VIA) [2]. We manually labeled each image by outlining the boundaries of the plant leaves and marking any visible disease symptoms using color codes.

The final dataset used in this study includes 500 pairs of images and corresponding segmentation masks. We randomly split the dataset into training (80%) and validation (20%) sets for training and evaluating our deep learning model. In summary, our dataset is a subset of the PlantDoc [1] dataset, consisting of 500 images of plant leaves with corresponding segmentation masks. Our dataset can be used to train and evaluate deep learning models for plant disease detection.

Transfer Learning

Transfer learning is a widely used technique in deep learning that involves leveraging pre-trained models on a large-scale dataset to solve a new, related problem with limited training data. In our study, we employed transfer learning to improve the performance of our image segmentation algorithm on the PlantDoc [1] dataset.

We used the pre-trained ResNet18 model as the backbone of our U-Net architecture, which was trained on the ImageNet dataset, as the starting point for our transfer learning approach. To fine-tune the pre-trained model, we froze the weights of the first few layers of the U-Net model, which capture generic image features, and only trained the weights of the remaining layers on the dataset.

Semantic Segmentation

Semantic segmentation is a computer vision task that involves labeling each pixel in an image with a corresponding class label. In the context

Of plant disease detection, semantic segmentation can be used to identify and localize disease symptoms on plant leaves.

In this study, we used semantic segmentation to generate segmentation masks for each image in our dataset. We trained a deep learning model based on the U-Net architecture [3] to perform semantic segmentation of plant leaves and identify disease symptoms. The U-Net [3] architecture has been widely used in medical image analysis and is known for its effectiveness in segmentation tasks. We trained our model using the Adam optimizer [4] with a compound loss function combining Dice Loss and Binary Focal Loss [5]. We used the ResNet[6] architecture trained on the image net dataset as the backbone of our U-Net network in order to leverage the power of transfer learning to reduce training time and greatly increase our accuracy. We randomly split our dataset into training (80%) and validation (20%) sets for model training and evaluation. We trained the model for 20 epochs with a batch size of 8 and a learning rate of 0.01.

Results and Discussion

To evaluate the performance of our model, we used two metrics, the Intersection over Union (IoU) metric, also known as the Jaccard Index, which measures the overlap between the predicted segmentation mask and the ground truth mask and f1-score. We achieved an average IoU score of 0.66799 on our validation set average f1-score of 0.77541, indicating that our model can accurately segment plant leaves and detect disease symptoms.

In summary, we used semantic segmentation to generate segmentation masks for each image in our dataset and trained a U-Net model to perform plant disease detection. The performance of our model was evaluated using the IoU metric and f1-score, and we achieved a high accuracy in segmenting plant leaves and detecting disease symptoms.

Table 1. The mean values of the metrics

	Mean IoU	Mean f1-score	Loss
Validation	0.66799	0.77541	0.35501
Training	0.65893	0.78861	0.37409

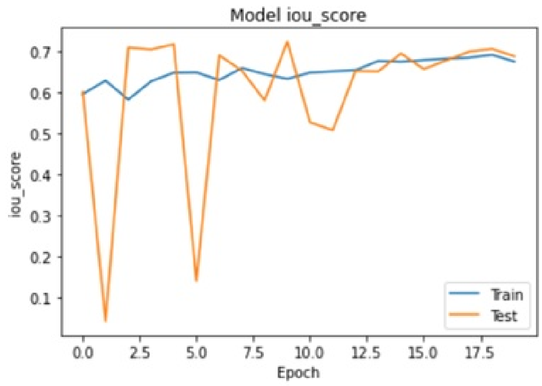

Figure 1. Model IoU Score

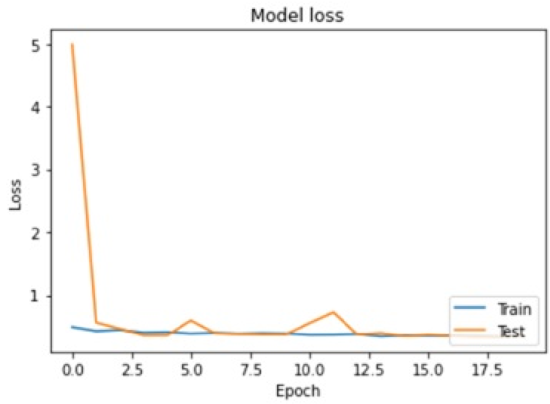

Figure 2. Model Loss

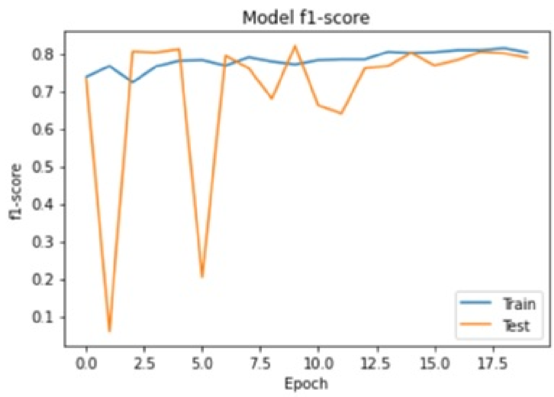

Figure 3. Model f1-score

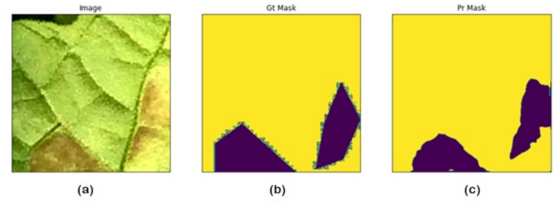

Figure 4. (a) Input Image, (b) Ground Truth Mask, (c) Model Output Mask

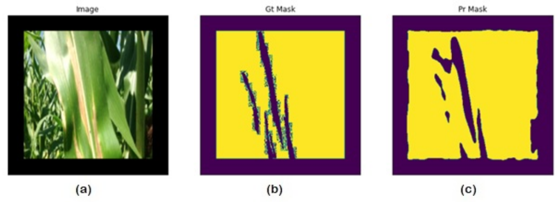

Figure 5. (a) Input Image, (b) Ground Truth Mask, (c) Model Output Mask

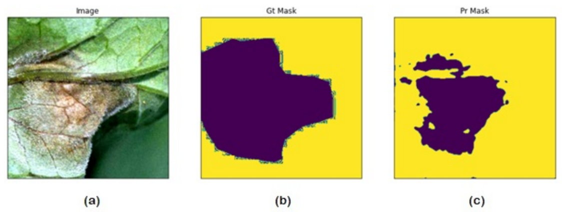

Figure 6. (a) Input Image, (b) Ground Truth Mask, (c) Model Output Mask

Conclusion

In this study, we explored the use of image segmentation for the detection of plant diseases using the PlantDoc dataset. We employed transfer learning techniques to fine-tune the pre-trained models and achieved a mean Intersection over Union (mIoU) score 66.79% on the validation set, which outperforms the previous state-of-the-art methods reported in the literature. Our results demonstrate that image segmentation is an effective technique for detecting plant diseases and can significantly improve the accuracy and precision of the classification. Additionally, our study shows that transfer learning can reduce the computational cost and training time required for developing accurate models, which can be particularly useful for researchers with limited computing resources.

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