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Enhancing Crop Health: A Review of Image Processing Methods for Leaf Disease Identification

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Abstract

This research presents an overview of different image processing techniques for the identification of leaf disease. Many algorithms can be used to identify and categorize leaf diseases in plants, and digital image processing provides a quick, dependable, and accurate method of disease detection. This paper presents various techniques used on multiple crops and the achieved accuracy for each model. Leaf disease detection is a critical task in agriculture to ensure the health and productivity of crops. Traditional methods of disease identification are often labor-intensive and subjective, highlighting the need for automated solutions. In recent years, deep learning techniques have emerged as powerful tools for automatic disease detection, offering the potential to revolutionize agricultural practices. Our work primarily focuses on analyzing several methods for detecting leaf disease and presents a summary of various image-processing methods. When given the resources and information required for early disease identification, farmers are more equipped to make informed decisions and act swiftly to prevent it. As a result, their total crop yield and income can rise. From the review we conclude that convolutional neural network models show the most accurate results with highest accuracy scores and are best suited for image processing because they employ the technique known as parameter sharing that makes them more structured while working with image data.

Keywords: Image processing, leaf disease, agriculture, pesticides, crop

INTRODUCTION

Agriculture is a vital component of India's economy, culture, and livelihood and is the backbone of the Indian economy. It is a major contributor to India's gross domestic product (GDP), employing most of the workforce. It accounts for about 17% to 18% of the country's GDP and provides livelihoods to over 50% of the population, especially in rural areas. India's diverse climate and topography allow for the cultivation of a wide range of crops. Plant disease disrupts a plant's regular growth, which is one of the main causes of lower production and subsequent financial losses. Leaf diseases pose a problem in the field of agriculture, impacting plants and crops on a large scale. These diseases primarily target the leaves of plants resulting in symptoms like changes in color, spots, drooping, and ultimately leading to decreased crop productivity. In India, where agriculture plays a role, in both the economy and food security it is crucial to detect leaf diseases at early stages. To maintain world populations and provide food security, agricultural crops must be in good health. Crop diseases, however, seriously jeopardize economic stability, quality, and production. Because they affect plant vitality negatively and are common among these diseases, leaf infections are especially problematic.

Conventional disease detection techniques, which depend on agronomists' manual inspection, are labor-intensive, time-consuming, and frequently

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subjective. Furthermore, the need for more scalable and effective solutions is made more urgent by the rising demand for food production.

The use of pesticides and fungicides to manage leaf diseases can have adverse effects on the environment. Detecting these diseases early allows for effective application of these chemicals, which helps minimize their impact, on the environment. It is more economical to detect and manage leaf diseases on than to deal with severe infections. The infected rice plants are photographed using digital cameras, and the resulting images are processed using image growth and image segmentation techniques to determine which parts of the plants are damaged. Four different types of images are used here for testing purposes, and trained images are created by deleting characteristics from the sick sections of the leaf. Taking action can stop the diseases from spreading and decrease the reliance, on treatments. Early detection of leaf diseases gives researchers vital information that they can use to comprehend disease trends, create resistant crop types, and enhance agricultural techniques. Long-term agricultural sustainability is enhanced by this. Farmers are better able to make educated judgments and quickly implement preventative actions when they are provided with the tools and knowledge necessary for early disease identification. Their overall crop output and income may increase as a result.

Recently, a number of methods have been put out to identify and classify plant diseases from photos using machine learning. Agriculture could be revolutionized by the use of deep learning for the early diagnosis of plant diseases. Deep learning, a subset of machine learning, involves the use of artificial neural networks to process and analyze data. DMS-Robust Alexnet maximizes the model's receptive field through the use of dilated convolution in the first layer, maximizing its extraction capacity while avoiding significant changes to the latter layer's parameters.

In this work, we aim to propose a system that would detect and categorize the plant diseases using deep learning. We will be using convolutional neural networks (CNNs) architecture which is a type of artificial neural network. For our project, we will be using the “plant village”. At the primary stage, we are going to limit our work to potato plants. Several steps are involved in the development of the prediction model which are data pre-processing, image segmentation, feature extraction, feature fusion, model training, and then testing. We chose CNN as it works best with classification problems.

LITERATURE REVIEW

Andrew et al. [1] used CNN-based pre-trained models to identify plant diseases. They adjusted the hyperparameters of popular pre-trained models, such as ResNet-50, VGG-16, DenseNet-121, and Inception V4. The popular dataset "Plant Village," which has close to 54000 photos, was used for the test. The F1 score, sensitivity, specificity, and accuracy of classification were used to evaluate the model's performance. Following a comparison examination, the tests showed that DenseNet-121 performed better than the most advanced models, with a 99.81% increase in classification accuracy.

To prevent output losses, Kibriya et al. [2] devised a technology that can be deployed in tomato fields to detect infections early. 10,735 photos from the dataset Plant Village were used to test the model. Three diseases are investigated using the image processing technique: bacterial spot, early blight, and late blight. GoogleNet and VGG16 are two models that use CNNs to classify tomato leaf diseases. The suggested goal of this work is to apply deep learning to identify the optimal solution for the tomato leaf disease detection problem. While GoogleNet attained 99.23% accuracy, VGG16 obtained 98%.

Phadikar and Sil [3] described a software prototype method for identifying rice diseases using diseased photos of different rice plants. Digital cameras are used to take pictures of the diseased rice plants, which are then processed utilizing image growth and image segmentation techniques to identify the affected plant portions. For testing reasons, four different types of pictures are employed here, and trained pictures are produced by removing features from the leaf's diseased areas. The diseased rice images are then recognized by utilizing a self-organizing map (SOM) neural network. Using a straightforward and computationally efficient method, the zooming algorithm collects features from the photos, leading to a good categorization for test images. Using RGB (red, green, blue) spots for categorization, this model achieves up to 92% classification accuracy.

Rothe and Kshirsagar [4] identified and categorized three cotton leaf diseases—Myrothecium, Alternaria, and Bacterial Blight—using a pattern recognition approach that is provided in the work that is suggested. This project uses photographs taken by the Central Institute of Cotton Research in Nagpur's fields. The picture segmentation process uses the active contour model. Three types of photos of infected leaves are utilized to identify the seven invariant moments that should be extracted in order to train a neural network based on back propagation that will subsequently categorize the pictures of sick cotton leaves. The average categorization accuracy is determined to be 85.52%. Although it is a very long procedure, the snake segmentation algorithm offers an effective way to localize an infected region. As a result, the system's training and testing phases are prolonged.

Jaisakthi et al. [5] have created a model for diagnosing illnesses in grape vines that makes use of machine learning and image processing. The suggested solution initially divides the leaf section from the backdrop employing the grab-cut segmentation technique. Using the segmented leaves, two different methods are employed to determine the sick zone. The global thresholding technique is used in the first strategy, and semi-supervised learning is used in the second approach. Among the dataset's photos, 80% were utilized for training and the rest for testing. The features are retrieved from the segmented sick part and classed as healthy, rot, esca, and leaf blight, and the findings are compared [5]. For classification, Adaboost, random forest, and support vector machine (SVM) algorithms were employed. With the use of SVM and global thresholding, an accuracy result of 93.035% was obtained.

Lv et al. [6] have created a framework for enhancing maize leaf features. After working with a dataset comprising 12,227 samples, they were able to classify the infections into six groups: fall armyworm, round spot, zinc deficiency, grey leaf spot, and common rust. Then, the backbone Alexnet design is used to develop a novel neural network called DMS-Robust Alexnet. The DMS-Robust Alexnet incorporates both dilated and multi-scale convolution to improve feature extraction efficiency. Batch normalization is used to improve the model's robustness and prevent over-fitting of the network. To improve accuracy and convergence, the PRelu activation function and the Adabound optimizer are employed. DMS-Robust Alexnet uses dilated convolution in the first layer to broaden the model's receptive field, maximizing its capacity for extraction while avoiding substantial changes to the latter layer's parameters. Furthermore, the incorporation of multi-scale convolution extraction features enhances the precision of disease identification at various phases of the disease by providing a more accurate characterization of various diseases [6]. The suggested approach yielded an accuracy of 98.62% when compared to other baseline techniques such as ResNet50 (accuracy 95.47%), GoogleNet (accuracy 94.05), and VGGNet (accuracy 93.98%).

In addition to General Cedar Apple Rust, General Apple Scab, Apple Gray Spot, and Serious Apple Scab, the dataset created for the article by Zhong and Zhao [7] contained 2462 images of apples in good health. These were employed in visualizing data and model assessment. Here, DenseNet-121 was the technique used. DenseNet-121 minimizes model parameters, promotes feature reuse, and improves feature propagation. Each network layer is connected directly to its front layer in order to facilitate feature reuse. In addition, each layer is specifically narrow, meaning that only a small number of feature mappings are learned in order to minimize recurrence [7]. Three techniques namely multi-label classification, regression, and focus loss function were presented to diagnose apple leaf diseases based on the Densenet-121 deep convolution network. On the test dataset, the three algorithms' accuracy rates were 93.31%, 93.51%, and 93.71%, respectively. Quantitative experiments showed that the above methods outperform the traditional single-label multiclassification method with cross-entropy loss function in terms of recognition results on the unbalanced data set [8–10].

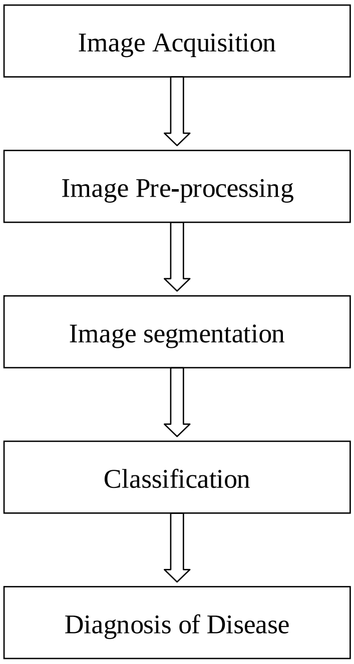

Figure 1. Process flowchart of developing a leaf disease detection algorithm.

Table 1. Accuracy is found in cropping methods used in crops.

S.N.	Title	Crop	Method	Accuracy
1.	Paper 1	Multiple	DenseNet-121	99.81%
2.	Paper 2	Tomato	Google net	99.23%.
3.	Paper 3	Rice	SOM (self-organized map)	92%
4.	Paper 4	Cotton	Back propagation	85.52%
5.	Paper 5	Grape	SVM	93.035%
6.	Paper 6	Maize	DMS-Robust Alexnet	98.62%
7.	Paper 7	Apple	DenseNet-121	93.51%

SUMMARY

From all the research that we have done, we found that the basic flow of the process of developing a leaf disease detection algorithm using machine learning is as shown in the flowchart (Figure 1). The accuracy is found in cropping method used in crop is shown in Table 1.

CONCLUSION

This paper provides a summary of image processing methods for leaf disease detection and classification. Various authors employed distinct techniques to accurately diagnose diseases. Identifying leaf diseases early on is one benefit of employing image processing techniques. The majority of researchers employed classifiers such as SVM, Densenet-121, and backpropagation to increase the recognition rate. These methods are employed to analyze the leaves of both healthy and sick plants. Every technique used in this paper produces effective results while saving time. A few of the difficulties with these methods include optimizing the method for a particular plant disease, the impact of background noise on the final image, and implementing the method for ongoing, automated monitoring of plant diseases in everyday life field settings. The research study comes to the conclusion that applying machine learning to disease detection has a lot of potential for identifying leaf diseases at early stages and preventing damage on a wider scale.

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