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Embarking Role of Convolutional Neural Network in Plant Disease: An Implementation

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Research Paper

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ABSTRACT

Detecting plant diseases is essential in agriculture, as identifying and diagnosing these issues early can help prevent significant crop losses. This paper outlines a system that employs Convolutional Neural Networks (CNN) to recognize and classify plant diseases using images of leaves. The system incorporates preprocessing methods for enhancing images, followed by a CNN model that extracts features and performs classification. It demonstrates high accuracy in identifying various plant diseases, making it a valuable resource for farmers and researchers aiming to monitor and manage crop health. The paper concludes that CNN-based systems for plant disease detection hold great promise for improving the efficiency and accuracy of diagnosis and treatment, ultimately contributing to better crop yields and enhanced food security.

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INTRODUCTION

Since prompt diagnosis and control of plant illnesses are critical, plant disease detection systems are becoming more and more important in agricultural research. Convolutional neural networks, or CNNs, have become more potent tools for classifying and recognizing images in recent years. In this work, we provide a CNN-based plant disease prediction system that reliably identifies and categorizes a range of plant illnesses from leaf photos. Three main parts make up the system: classification, feature extraction, and picture preprocessing. Leaf photos undergo processed in order to improve contrast and remove background noise. The CNN model finds pertinent features in the processed pictures during the feature extraction stage. Ultimately, these characteristics are used to identify the kind of plant disease at the classification stage. To evaluate the efficacy of our system, we experimented with a collection of photos of leaves that depicted various plant illnesses. The findings show that our method has a low error rate and excellent precision in predicting the types of plant diseases. Farmers and researchers can quickly detect and treat plant illnesses with the help of this instrument, which will eventually increase agricultural production and food security.

METHODOLOGY

The dataset We make use of the plant village dataset, which includes 20,639 photos of bell paper, tomatoes, and potatoes with healthy and diseased leaves. After the image has been compressed to 256 x 256 pixels, it is optimized and model predictions are generated.

Leaf category	Number of Images of size 256X256
Tomato	16012
Potato	2152
Bell pepper	2475
Total	20639

Table 1: Total No.of Leaves

Leaf category	Healthy leaf	Diseased leaf
Tomato	1591	14421
Potato	152	2000
Bell- pepper	1478	997

Table 2: No.of Healthy and Diseased Leaves

Figure 1 Healthy Leaves

Figure 2 Diseased Leaves

Data Processing and Augmentation

Image augmentation is a necessary component of a successful image classifier. Hundreds to several thousand training examples may be present in datasets, however this variety might not be sufficient to create a reliable model. Images may be resized, rotated at different angles, and flipped both vertically and horizontally, among other picture improvement techniques. These methods aid in enlarging the dataset's pertinent information. Notably, every picture in the Plant Village collection is 256 × 256 pixels in size. The deep-learning framework Keras is used for picture improvement and data processing. During training, the following augmentation strategies are used:

1. Rotation: A training image rotated at random from different angles.
2. Brightness: The model benefits from training with photos of varying brightness levels to adjust to changes in illumination.
3. Shear: Adjusting the angle of shearing

PROPOSED SYSTEM

Convolutional neural networks (CNNs) prefer deep learning models because they can learn significant information from input images at different convolutional levels, which is similar to how the human brain functions. These models achieve high classification rates with little mistakes, making them capable of swiftly and accurately tackling complicated issues. Convolutional layers, pooling layers, fully connected layers, and activation layers are some of the elements that make up a deep learning model's architecture. The number of layers and parameter sizes for different CNN models are listed in Table 3. For example, Inception contains 48 layers and 27 million parameters, whereas ResNet50 has 50 layers and 25.6 million parameters. In contrast, MobileNet-V2 has 3.37 million parameters and 28 layers. In our investigation, we used a ResNet50 pretrained model.

Table 3 Comparison among different CNN architectures regarding layer number and parameter size

Model	No. of Layers	Parameters (million)
ResNet50	50	25.6
InceptionV3	48	27
MobileNetV2	28	3.37

Training and Testing Data

Fig 3 shows the block diagram illustrating the training process of CNN.

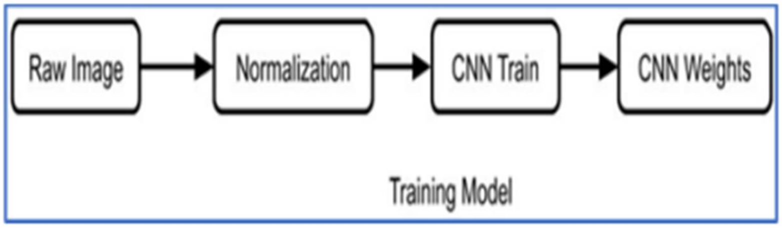

Figure 3 Training Model [6]

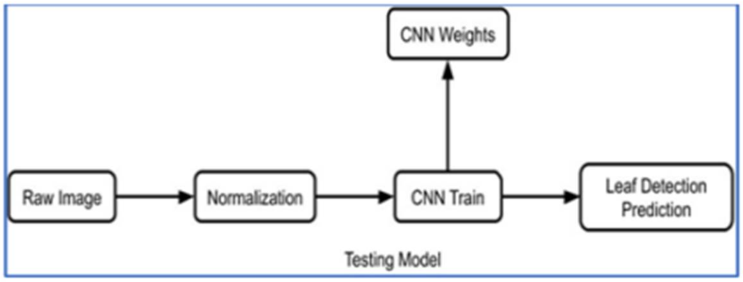

Figure 4 Testing Model [6]

A raw image serves as the CNN's input at the start of the training phase. Pixel values that indicate intensity or color information make up this raw image.
2. Normalization: To improve training effectiveness and performance, normalization techniques are frequently used prior to the raw image being fed into the CNN. To ensure that the input data maintains a consistent scale and distribution, this entails scaling the pixel values to a specified range, such as [0, 1] or [-1, 1]. In order to keep some features from overpowering others during the learning process, this phase is essential.

3. CNN Training: Next, the CNN is trained using the normalized image. Convolutional layers, pooling layers, activation functions, and other layers make up the CNN layers that might be completely connected. Through an iterative process that involves forward propagation, backpropagation, loss computation, and parameter adjustments, it seeks to learn and extract important features from the input image. Before the model's performance stabilizes or reaches a satisfactory level, this cycle is repeated over a number of epochs.

4. CNN Weights: To reduce the loss function and improve the model's performance, the CNN's weights (or parameters) are gradually changed during training. The CNN's learnt patterns and characteristics are embodied by these weights. The CNN model has optimized weights after training, which represent the

insights gleaned from the training dataset. The learned representations are embodied by the trained CNN model and its weights, which may be used for a variety of tasks such as object identification, picture segmentation, and image classification. These training weights enable the model to produce precise predictions on novel, unseen images by reflecting the network's comprehension of the salient characteristics and connections present in the input data. The block diagram that describes the CNN's testing procedure is shown in Figure 4.

1. Raw Image: A leaf that needs to be examined for disease detection is shown in a raw image at the beginning of the testing procedure.

2. *Normalization:* To guarantee uniform pixel value scaling and distribution, the raw image is normalized, just as it was during the training stage. To improve performance and image comparability, this step is essential during testing.

3. *CNN Training*: Prior to testing, a labeled dataset containing pictures of both healthy and diseased leaves is used to train the CNN model. Normalized images are supplied into the CNN during this training phase, and the weights of the model are iteratively changed to discover the characteristics that differentiate healthy leaves from diseased ones. These learned patterns are intended to be generalized to new images by the CNN.

4. *CNN Weights:* The CNN model has optimal weights that capture the learnt features and representations once the training phase is finished. These weights represent the information the model has learned about the characteristics that differentiate healthy from unhealthy leaves during training.

5. *Leaf Disease Detection:* The normalized raw image is processed during the testing stage. via the CNN model that has been trained and fitted with its learning weights. The model applies the acquired features and patterns to the input image through forward propagation. After then, the CNN generates a prediction or probability score that shows how likely it is that the leaf will be infected. Early detection and prompt action are made possible by this output, which is crucial in determining the kind and presence of illness in the leaf. An important part of this procedure is the trained CNN model with its optimal weights. A convolutional neural network (CNN) architecture with 50 layers is called ResNet-50, or Residual Network-50. It was created in 2015 by Microsoft Research engineers, and since then, it has become

quite popular and influential in a variety of computer vision applications, including object identification, picture segmentation, and image classification. The arrangement of A global average pooling layer, a fully connected layer for classification, and a sequence of convolutional layers make up ResNet-50. The "residual block" is a crucial part of the architecture, which is divided into various blocks. In order to enable the network to learn residual mappings instead of the goal mappings directly, this block usually consists of two or three convolutional layers joined by shortcut connections that omit the intermediary layers. Large picture datasets such as ImageNet, which contains millions of tagged images, have been used to pre-train ResNet-50. This pre-training aids in the network's acquisition of rich and discriminative features that can be refined on particular datasets with fewer labeled samples or applied to other related tasks.

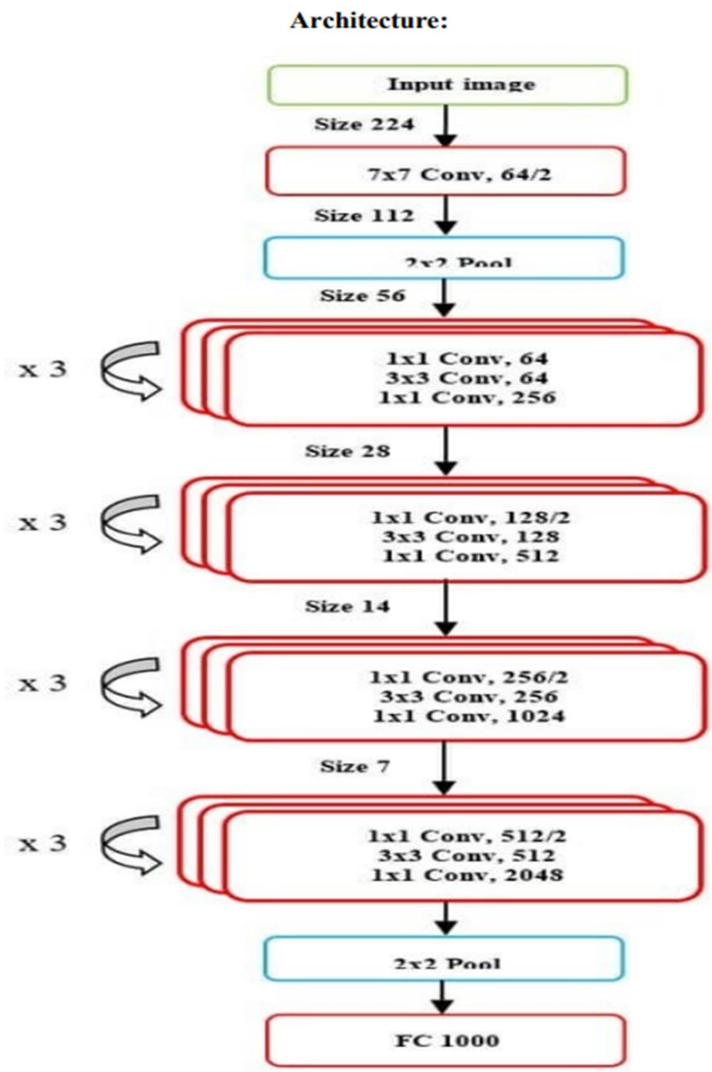

Figure 5: ResNet CNN Architecture

RESULT

A workable and profitable solution for disease detection is still lacking, despite the numerous sophisticated techniques for identifying and categorizing plant diseases based on the examination of sick leaves. Even while research and academia have made significant strides, the difficulty is in turning these developments into workable solutions that meet business requirements including scalability, real-time performance, ease of use, and compatibility with current agricultural methods. Using photos of both healthy and diseased leaves, we investigated the application of three distinct deep learning models—InceptionV3, ResNet50, and MobileNetV2—to the detection of plant illnesses. ResNet50 continuously produced remarkable training accuracy, validation accuracy, and test accuracy, according to an analysis of the data in Table 4. As a result, we decided to use the convolutional neural network ResNet50.

Table 4 Comparison of Train Accuracy and Train Loss among Different CNN Models

Model	Train acc (%)	Train Loss
ResNet50	97.99	0.2316
InceptionV3	88.32	27.214
MobileNetV2	96.28	0.545

Table 5 Comparison of Validation Accuracy and Validation Loss among different CNN models

Model	Validation acc (%)	Validation Loss
ResNet50	96.68	2.031
InceptionV3	74.84	104.009
MobileNetV2	89.86	2.053

Table 6 Comparison of Epoch and Average time among different CNN models

Model	Epoch	Avg time (s/epoch)
ResNet50	10	286.8
InceptionV3	10	364.7
MobileNetV2	10	150.4

Table 7 Comparison of Test accuracy and Test loss among different CNN models

Model	Test acc (%)	Test Loss
ResNet50	96.73	2.327
InceptionV3	75.29	105.199
MobileNetV2	88.84	3.022

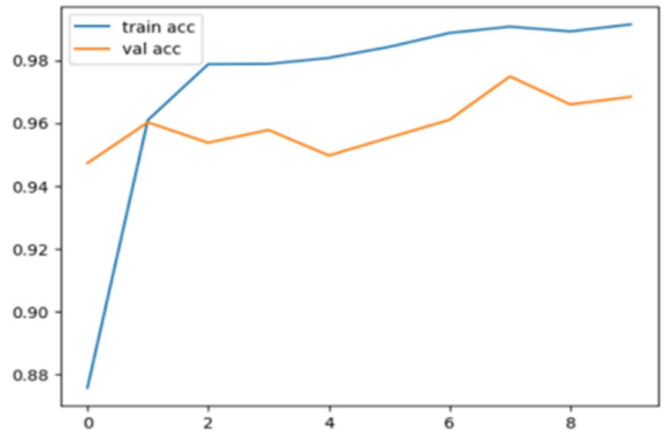

Figure 6 Training accuracy vs Validation accuracy

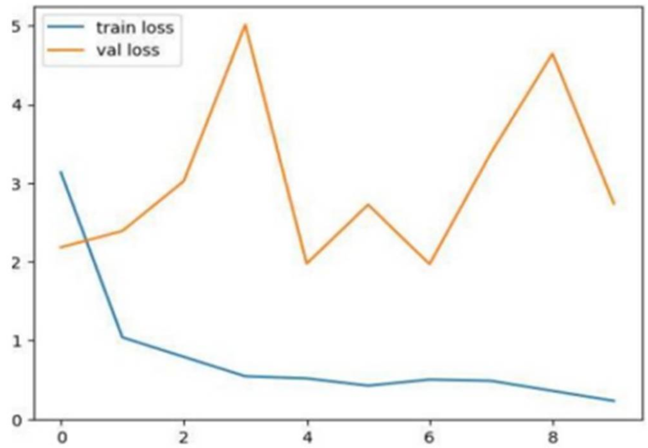

Figure 7 Training loss vs Validation loss

CONCLUSION

We have successfully developed methods for categorizing diseases that can be used to identify plant leaf diseases. A deep learning model has been created to automatically recognize and classify these diseases. We tested the proposed approach on three species: tomato, potato, and bell pepper. This allowed us to perform various image-processing tasks. Furthermore, we utilized the data to construct the ResNet50 model, a sophisticated convolutional model, and trained it for accurate predictions. Our model achieved an impressive accuracy rate of 96.7%.

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