Leaf Disease Detection Using Deep Learning

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Abstract. Leaf disease detection uses a technology that can identify the disease of a leaf or plant and, in response, provide the best solution to overcome the disease in order to provide us with an appropriate remedy that can be utilized as a defensive mechanism against the disease identified. Agriculture being a very significant part of many developing nations. As a result, it becomes essential to recognize infected plant leaves and categorize diseases in order to prevent serious plant loss. With faster and more precise answers, the loss of farmers can be avoided. There are four steps to determining the type of disease: picture preprocessing, feature extraction, classification, and diagnosis Convolution Neural Network (CNN), which consists of various layers utilized for prediction, is used for categorization and image preprocessing to enhance the quality of the image. A cure is advised for the user at the final stage.

Keywords: Convolutional neural network (CNN) · Image Feature Extraction · Classification

1 Introduction

The most crucial aspect of agriculture's quality is how something looks on the outside. The selling price and purchasing behavior of any item are significantly influenced by its exterior appearance. As a result, grading systems and quality control are essential for growing strong, healthy plants in the agricultural sector. Plant diseases can cause considerable loss of productivity and financial costs in the agricultural industry. It's challenging to handle this condition. The plant's leaves or stems frequently display signs of their diseases, such as bright spots or stripes. A variety of fungi, bacteria, and viruses are to blame for the bulk of plant leaf diseases. A number of visual symptoms are used to describe the sickness these organisms cause on plant leaves or stems. Numerous diseases that harm plants and whose initial symptoms may not be immediately visible generate societal and economic losses. By detecting the color features of the leaves, the image processing helps identify diseases and offers preventive for some of them. It is essential for detecting plant diseases since it produces the greatest results with the least amount of human effort. This paper's goal is to review various methods for identifying plant diseases and to compare them in terms of various criteria. There are four sections to this essay. The need and significance of plant disease detection is briefly discussed in the first section. The techniques are covered in the second section, which also displays

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recent work that has been done in this field. The fundamental procedures used to create a disease detection system are detailed in the third part. The fourth portion wraps up this essay.

2 Literature Review

Mohanty et al. have focused on the GoogleNet and AlexNet CNN architectures. About 54,306 photos of various plants representing 38 distinct kinds of illnesses were acquired for the dataset, which was taken from the Plant Village collection. The photos in dataset were scaled down to 256 by 256 pixels. On these scaled photos, the predictions and model optimization were then carried out. The dataset is split into training and testing in the ratio of one to four, and each process is conducted for a total of 30 epochs [1].

Kulkarni et al. have created a system that accurately detects plant diseases by using artificial neural networks and a variety of image-processing methods. The technique obtains a recognition rate of up to 91% by combining the Gabor filter for feature extraction with the ANN classifier for classification [2].

Vijayaraghavan et al. have argued that a support vector machine is a very effective AI technique that can be used to address classification-related issues. The SVM used to tackle regression issues is called Support Vector Regression (SVR). SVR is well known among scholars for giving the solution model the ability to be generalized [3].

Gayatri Kuricheti et al. established a highly effective algorithm for the detection and mitigation of illnesses spreading across the entire crop. The dataset's photographs were processed using K-Means image segmentation, and the leaf image textures were examined using GLCM. An SVM classifier is then used to categorize the feature derived from those photos after their attributes are ranked using an information gain approach. K-Means clustering has a set number of created clusters, whereas three clusters are optimum. This is its main disadvantage. The healthy leaf portion, the infected portion, and the backdrop are each shown by a cluster [4].

Peng Jiang et al. have shown a selection of infected pictures of apple leaves taken in actual fields. The dataset is prepared using tools for data augmentation and annotation. The Google Net Inception structure as well as Rainbow concatenation are used as deep CNNs for the detection of apple leaf disease. A dataset of 26,377 pictures of infected leaves are used to train the suggested model. The model is good for identifying rust, mosaic, grey spots, brown spots, and Alternaria leaf spots [5].

Khamparia et al. 2019 used convolutional neural networks (CNN) to identify traits of diseases in crops. It also uses autocoder to identify disease. The study team examined a dataset of 900 images of three crops with five different types of diseases, including rust disease in maize, leaf molds in tomatoes, yellow leaf curl, and early and late blight in potatoes. For different convolution filters of sizes 2 X 2 and 3 X 3, for different numbers of epochs, and for different convolution filters, the accuracy varies. When training, Adam Optimizer has been utilized to lower loss and increase accuracy [6].

In 2019, Kamal et al. proposed two depthwise separable convolution models—Modified MobileNet and Reduced MobileNet—and evaluated how well they performed against MobileNet, AlexNet, and VGG.

Among the optimizers employed were SGD, Adam, and Nadam. In terms of performance and convergence rate, Nadam fared better than the other two optimizers. A total

of 82,161 images from the publicly accessible PlantVillage dataset, which contains 55 distinct classes of healthy and diseased plants, were used for the model's training and testing [7].

G. Geetharamani and A. Pandian in 2019 came up with a deep convolutional neural network-based method for identifying plant leaf diseases. The authors use open-source data taken from the PlantVillage dataset to train and evaluate the Deep CNN architecture. 54,448 images of 13 different plant leaves were used in this study. An enhanced picture dataset and an unaugmented image dataset were used to train the model. The upgraded photos were created using gamma correction, color augmentation, noise injection, rotation, principal component analysis (PCA), and picture flipping, bringing the total number of images in the augmented dataset to 61,486 [8].

3 Proposed Methodology

The block diagram shown in Fig. 1 includes three stages. The initial stage of data collection and transmission is primarily in charge of gathering data from digital camera photos. Mobile devices, etc., in the chosen size and resolution. Images from the training set's dataset Initially, the model architecture was created with excellent accuracy in mind. The dataset utilized for the learning procedures was chosen and prepared in the following stage. The training dataset was employed in the third step of the process, after which the model was tested or validated using various photographs. Finished by placing the model for use on a web page. As a result, the output system data will determine whether the symptoms are manifesting on the plant's leaf and take the appropriate action. The digital camera image to be uploaded will be used, and we will use the CNN algorithm to run, which will reveal the findings on whether the plant is healthy or infected and classify the disease and assist the farmer in taking the appropriate action based on the disease kind.

3.1 CNN Model

The CNN model is employed for disease detection and categorization. The four layers in this model are the input layer, the convolutional layers, the pooling layers, the fully connected layers, and the output layer. The TensorFlow library and the Python programming language are used to implement the model. The model that was used for the detecting system is shown in Table 1 and Fig. 2.

The four layers that are present in model design contribute in a CNN model. The CNN name and its main layer are derived from the convolutional layer. It is utilized to separate the feature map from the input image before employing filters to build a new matrix with a smaller size. The first layer in the suggested model utilizes a 7x7 filter, the biggest filter size in the model, to represent the overall features of the input image, followed by a convolutional layer that uses a 5x5 filter and two final layers that use a 3x3 filter. After the matrix had been convoluted through all convolutional layers, the SoftMax activation function was applied. The pooling layer compresses the output matrix of the preceding convolutional layer. Each tier of the pool receives application of the Max pooling function. 5 x 5 is the size of the pooling layer filter. The SoftMax function, which has three neurons, is used to activate the output layer. For the design

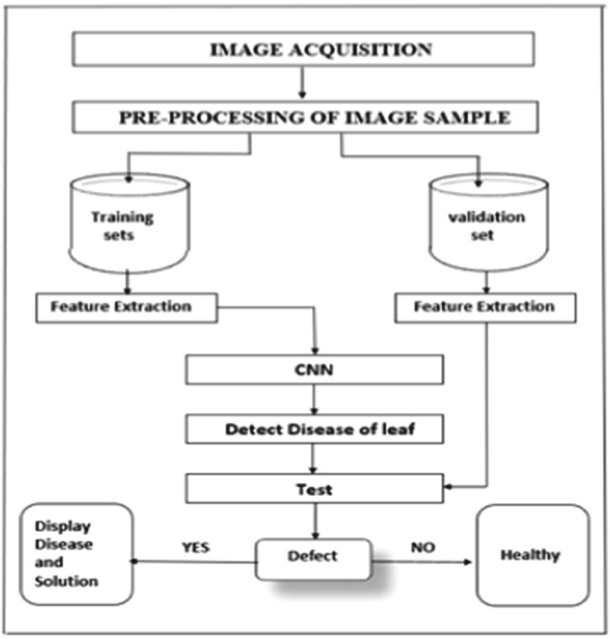

Fig. 1. Block Diagram of leaf disease detection using deep learning

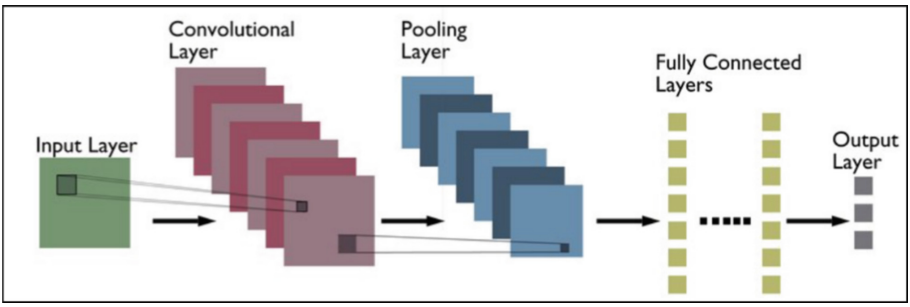

Fig. 2. CNN model architecture

and implementation of the model architecture, Python-based libraries TensorFlow and Keras were employed. To increase computing and graphics power, a model architecture was put into place.

3.2 Dataset

The photo of maize leaves form the Kaggle dataset were the source of the study's dataset. For classification, there are just three classes employed. The disease related three leaf image classes Northern Early Blight [1], Common Rust [2], and Healthy corn leaves [3] have contaminated the classification system. Samples of disease and healthy leaves from the dataset are shown in the figure.

Table 1. CNN Model Details.

Layer Type	*Weight Filter Size*	*Output Shape*
Input Layer	–	*3x256x256*
Convolution Layer 1 *Pooling Layer 1*	*7x7* *3x3*	*32x250x250* *32x83x83*
Convolution Layer 2 *Pooling Layer 2*	*5x5* *2x2*	*32x79x79* *32x39x39*
Convolution Layer 3 *Pooling Layer 3*	*3x3* *2x2*	*64x37x37* *64x18x18*
Convolution Layer 4 *Pooling Layer 4*	*3x3* *2x2*	*128x16x16* *128x8x8*
Fully Connected Layer 1	–	*128*
Fully Connected Layer 2	–	*128*
Output Layer	–	*3*

A total of 3000 colored or RGB leaf images with a resolution of 256x256 pixels make up the dataset used for the proposed system. There are 1000 photographs of the healthy leaf, 1100 images of leaves with Common Rust, and 900 images of leaves with Northern Leaf Blight. Before the training and testing operations began, the dataset was required to be prepared and preprocessed. In order to read the photos from the dataset, all of the photographs belonging to the same class were first collected in a single file with the class name. Next, the image is resized to 256x256 pixels using the Keras preprocessing tool. Third, the read images were transformed into arrays because the input layer of the model was introduced as an array. The fourth step involved labeling each image with the class name it belongs to. The dataset is divided into training group, validation group, and then testing groups.

4 Conclusion

One of the biggest challenges to global agriculture is crop diseases, which can cause up to 25% yearly losses in agricultural output. This study proposes a diagnosis and detection method for diseases of corn leaves based on a customised model architecture and convolutional neural network technology. The main objective of the proposed method is to identify infections in plants as soon as possible to minimize plant production losses brought on by diseases like Northern Leaf Blight and Common Rust of maize crops Three thousand colored photographs of maize leaves made up the dataset that was used to train and assess the algorithm. For model validation, the dataset was split into three sections: 70% for training, 25% for validation, and 5% for model testing. The accuracy dropped by 10% when the dataset was reduced from 1500 to 300 images, but it practically held steady when it was raised from 1500 to 3000 images. The proposed model architecture provides 99.52% accuracy compared to previous methods. The utilized method is compared to the VGG16 methodology using the same dataset, and the comparison

results show that our suggested system method outperforms the accuracy generated by the specified method.

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