Plant Leaf Detection and Disease Recognition using Deep Learning

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Abstract

The latest improvements in computer vision formulated through deep learning have paved the method for how to detect and diagnose diseases in plants by using a camera to capture images as basis for recognizing several types of plant diseases. This study provides an efficient solution for detecting multiple diseases in several plant varieties. The system was designed to detect and recognize several plant varieties specifically apple, corn, grapes, potato, sugarcane, and tomato. The system can also detect several diseases of plants.

Comprised of 35,000 images of healthy plant leaves and infected with the diseases, the researchers were able to train deep learning models to detect and recognize plant diseases and the absence these of diseases. The trained model has achieved an accuracy rate of 96.5% and the system was able to register up to 100% accuracy in detecting and recognizing the plant variety and the type of diseases the plant was infected.

Keywords: plant disease recognition, deep learning, computer vision, convolutional neural network

Introduction

Early plant disease detection plays a significant role in efficient crop yield. Plant diseases like black measles, black rot, bacterial spot, etc. affect the growth, crop quality of plants and economic impacts in the agriculture industry. To avoid the impact of these diseases, expensive approaches and the use of pesticides are some solutions the farmers usually implement. The use of chemical means damages the plant and the surrounding environment. In addition, this kind of approach intensifies the cost of production and major monetary loss to farmers. Early discovery of diseases as they occur is the most important period for efficient disease management. Manual disease detection through human experts to identify and recognize plant diseases is a usual practice in agriculture [1]. With the improvements in technology, automatic detection of plant diseases from raw images is possible through computer vision and artificial intelligence researches [2]. In this study, the researchers were able to investigate plant diseases and pest's infestation that affects the leaves of the plants.

Image processing techniques are now commonly employed in agriculture and it is applied for the detection and recognition of weeds [3], fruit-grading [4], identifying and calculating disease infestations of plants [5], and plant genomics [6]. Currently, the introduction of deep learning methods turns out to be popular [7].

Deep learning is the advanced methods of machine learning that uses neural networks that works like the human brain [8]. Traditional methods involve the use of semantic features as the classification method [9]. LeChun et al. describes deep learning as a neural network learning process and one feature of deep learning is that it can automatically obtain features through image patterns [10].

A convolutional neural network (CNN) is a deep learning model that is widely used in image processing. The work of Lee et al. [11] presents a hybrid model to obtain characteristics of leaves using CNN and classify the extracted features of leaves. The study of Ferentinos, K.P. uses simple and infected plant leaf images to detect plant diseases using pre-trained CNN model [12]. Durmus et al work on the detection of diseases of the tomato leaves using AlexNet and SqueezeNet pre-trained CNN architectures [13]. While Atabay et al. [14] contributed a new CNN architecture to do disease classification and identification.

The methodology in the study involves three key stages: acquisition of data, pre-processing of data and image classification. The study utilized dataset from Plant village dataset [15] that contains plant varieties of apple, corn, grapes, potato, sugarcane, and tomato. There are 11 types of plant diseases identified in the study including healthy images of identified plants. Image pre-processing involves re-sized images and enhancement before supplying it for the classification model.

Convolutional Neural Network

Deep learning is a subsection of Artificial Intelligence and machine learning that uses artificial neural networks (ANN). Training the deep learning models divides the feature extraction and extracts its features for classification. There are several applications of deep learning which include computer vision, image classification, restoration, speech, video analysis, etc.

A convolutional neural network with nominal process can simply detect and categorize. It is efficient in evaluating graphical images and extracts the essential features through its multi-layered structure. As shown in Fig. 1, the CNN involves four layers, that is: input image, convolutional layer and pooling layer, fully connected layers, and output.

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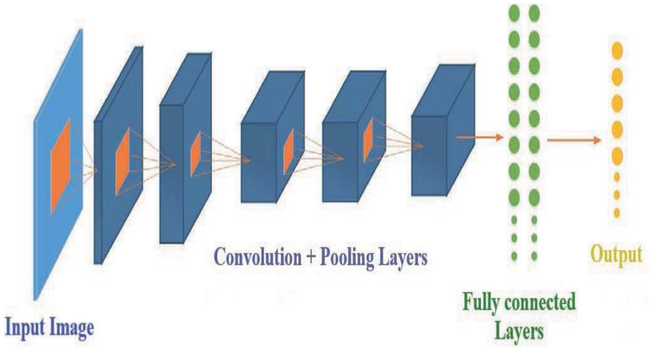

Fig 1. Illustration of Convolutional Neural Network Architecture

A. Convolutional Layer

Convolutional layers store the output of the kernels from the previous layer which consists of weights and biases to be learned. The generated kernels that represent the data without an error is the point of the optimization function. In this layer, a sequence of mathematical processes is done to extract the feature map of the input image [16]. Fig. 2 exhibits the operation of the convolution layer for a 5x5 image input and a result is a 3x3 filter that reduced to a smaller size [17]. Also, the figure shows the shifting of filter starting from the upper left corner of the input image. The values for each step are then multiplied by the values of the filter and the added values are the result. A new matrix with the reduced size is formed from the input image.

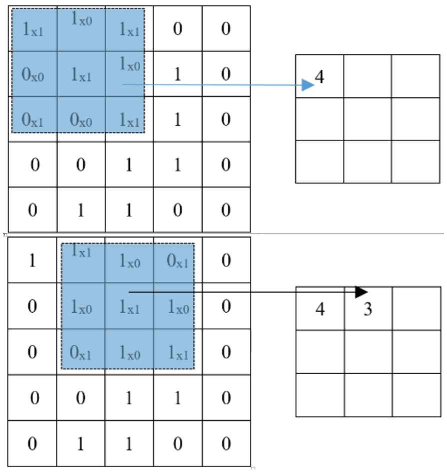

Fig. 2 5x5 input and 3x3 filter operation of convolution layer.

B. Pooling Layer

This layer reduces overfitting and lowers the neuron size for the downsampling layer. Fig. 3 illustrates an example of the pooling operation. This layer reduces the feature map size, reduce parameter numbers, training-time, computation rate and controls overfitting [20]. Overfitting is defined by a model by achieving 100% on the training dataset and 50% on test data. ReLU and max pooling were utilized to lower feature map dimensions [21].

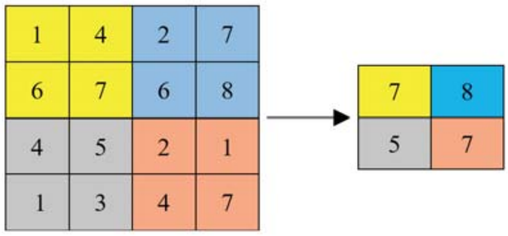

Fig. 3. Pooling operation

C. Activation Layer

Utilizes a non-linear ReLU (Rectified Linear Unit) activation layer in every convolution layer. The application of dropout layers to prevent overfitting is also applied in this layer.

D. Fully Connected Layer

This layer is used to analyze the class probabilities and the output is the input of the classifier. Softmax classifier is the well-known input classifier and recognition and classification of sugarcane diseases are applied in this layer.

Methodology

A block diagram presented in Fig. 4 shows the Input Dataset, Image Acquisition, Image pre-processing and Classification.

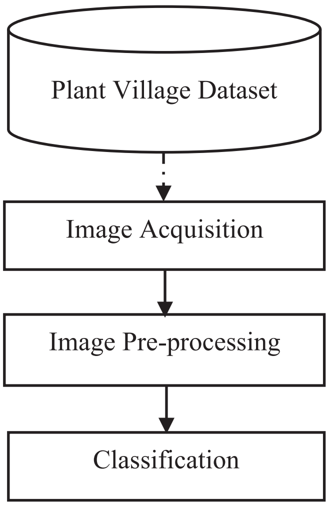

Fig. 4 Plant leaf detection and disease recognition methodology

A. Image Acquisition

Image dataset used for training the model was acquired in the Plant Village repository [15]. A python script was used to download images of the plant diseases from the repository. The acquired dataset consists of approximately 35,000 images with 32 different classes plant varieties and diseases.

B. Image Pre-processing

Pre-processed images are reduced image size and image crop to a given input. It processes and enhances the image to its needed color scale. The study uses colored and resized images to 96x96 resolution for processing.

C. Classification

Classification uses a fully connected layers and for feature extraction it uses convolutional and pooling layers. The classification process classifies the plant leaf if it is infected

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with the disease or not, identifies the type of plant disease and recognize the plant variety.

Experimental Settings

The dataset consists of approximately 35,000 images containing 9 different types of tomato leaf diseases, 4 different types of grape leaf diseases, 4 different types of corn leaf diseases, 4 different types of apple leaf diseases, and 6 different types of sugarcane diseases. A neural network application program interface (API) written in Python was applied for the CNN model application. All the image dataset was used for training and testing uses 1,000 images that was taken from the field. Data augmentation techniques were integrated into the application to enhance the image dataset by rotating the images to 25 degrees, flipping and shifting of images horizontally and vertically. Adam optimizer is incorporated using a categorical cross-entropy. The model trained 75 epochs using a batch size of 32. All the experimentations were performed on Dell Inspiron 14-3476 i5 processor and memory size of 16GB.

Results and Analysis

A 96.5% accuracy rate was achieved using 75 epochs during the training of the model. The model also achieved a maximum accuracy rate of 100% when testing random images of plant varieties and diseases. The visualization of plots of train and test accuracy is described in fig 5. shows the model is effective in detecting and recognizing plant diseases.

Fig. 6 shows of detection and recognition of a corn plant with 100% accuracy and it shows an accuracy rate of 100% recognition of healthy plant leaf on the left image and 99.56% affected with gray leaf spot disease on the right image. Fig. 7 shows the result of 99.77% and 99.58% accuracy of detecting and recognizing a tomato plant and it shows a 99.62% accuracy rate that it is infected with a late blight disease on the left image and 75.36% infected of early blight disease on the right image. Fig. 8 shows a 100% result of detection and recognition of a grape plant and shows a 100% rate that the leaf is infected with a late blight disease on the left image and 95.09% infected with a black rot disease on the right image. Fig. 9 shows the result of the detection and recognition of an apple plant with 100% accuracy and shows a 100% result that the leaf is infected with a black rot disease on the left image and a 99.99% that it is a healthy leaf on the right image.

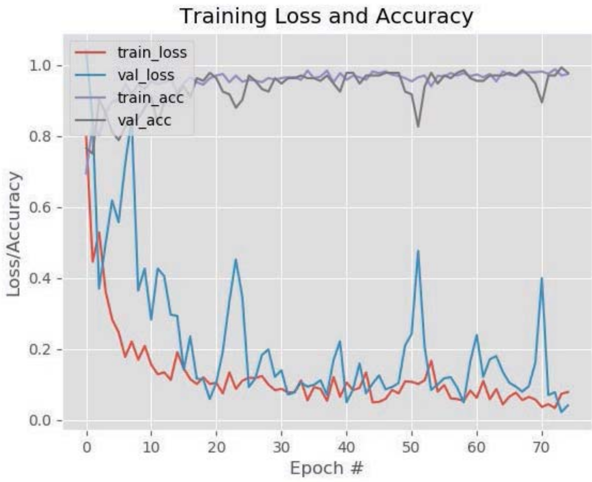

Fig. 5 Accuracy and loss against epochs

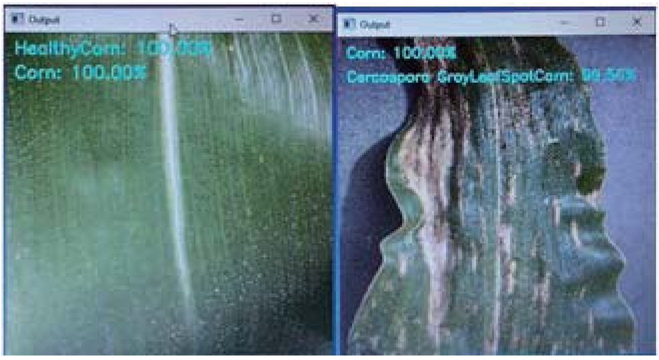

Fig. 6 Result of detection and recognition of a corn plant with 100% accuracy and shows a healthy plant leaf on the left image and diseased infected plant on the right image.

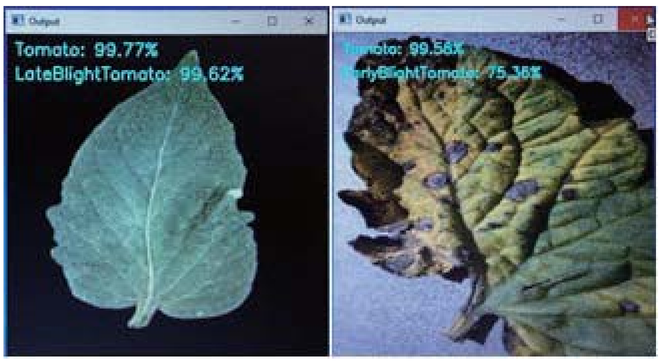

Fig. 7 Result of detection and recognition of a tomato plant with 99% accuracy and shows a leaf infected with a late blight disease on the left image and early blight disease on the right image.

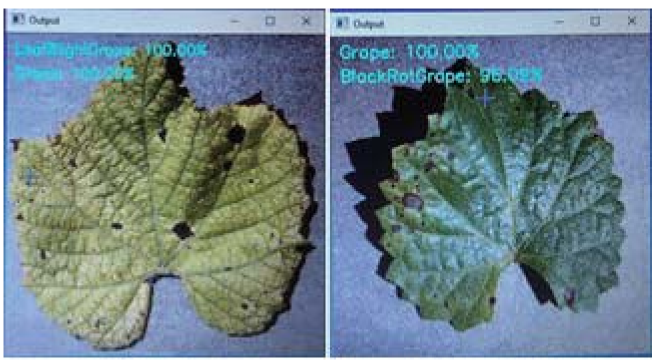

Fig. 8 Result of detection and recognition of a grape plant with 100% accuracy and shows a leaf infected with a late blight disease on the left image and black rot disease on the right image.

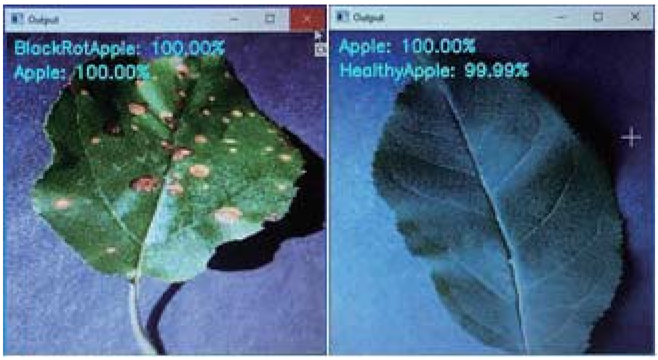

Fig. 9 Result of detection and recognition of an apple plant with 100% accuracy and shows a leaf infected with a black rot disease on the left image and a healthy leaf on the right image.

Conclusion

The people around the world rely on the agricultural sector as one of the most important sectors where crops are the basic need for food. Early recognition and detection of these diseases are crucial to the agricultural industry. This paper has achieved its goal to detect and recognize 32 different plant varieties and plant diseases using convolutional neural network. The trained model can be used to test real-time images to detect and recognize plant diseases. For the future work, additional plant varieties and different types of plant diseases may be included in the existing dataset to increase the trained models. Other CNN architectures may also use different learning rates and optimizers for experimenting the performance and accuracy of the model. With the achieved accuracy of 96.5%, the proposed model can assist farmers to detect and recognize plant diseases.

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