Perspective

iMedPub Journals
www.imedpub.com

Research Journal of Plant Pathology

2023
Vol.6 No.3:175

Identification of Picture Based Plant Illness

Xing Hung*

Department of Science and Technology, University of Peking, Beijing, China

Corresponding author: Xing Hung, Department of Science and Technology, University of Peking, Beijing, China, E-mail: Hung_X@gmail.com

Received date: August 18, 2023, Manuscript No. IPRJPP-23-18015; **Editor assigned date:** August 21, 2023, PreQC No. IPRJPP-23-18015 (PQ); **Reviewed date:** September 04, 2023, QC No. IPRJPP-23-18015; **Revised date:** September 11, 2023, Manuscript No. IPRJPP-23-18015 (R); **Published date:** September 18, 2023, DOI: 10.36648/iprjpp.6.3.175

Citation: Hung X (2023) Identification of Picture Based Plant Illness. J Res Plant Pathol Vol.6 No.3: 175.

Description

The occurrence of plant diseases has negative effects on agricultural production, and if the plant diseases are not detected in time, there will be an increase in food insecurity. In particular, the main crops such as rice, maize, *etc*., are essential for guaranteeing the food supply and agricultural production. The early warning and forecast are the basis of effective prevention and control for plant diseases. They play crucial roles in the management and decision-making for agricultural production. Until now, however, the visual observations of experienced producers are still the primary approach for plant disease detection in rural areas of developing countries; this requires continuous monitoring of experts, which might be prohibitively expensive in large farms. Besides, in some remote areas, farmers may have to go long distances to contact experts, which makes the consulting too expensive and time-consuming. Nevertheless, this approach can only be done in limited areas and cannot be well extended. Automatic recognition of plant diseases is an essential research topic, as it may prove benefits in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves. Therefore, looking for a fast, automatic, less expensive and accurate method to perform plant disease detection is of great realistic significance.

Image Identification

Plenty of previous works have considered the image recognition, and a particular classifier is used which categorizes the images into healthy or diseased images. Generally, the leaves of plants are the first source of plant disease identification, and the symptoms of most diseases may start to appear on the leaves. In the past decades, the primary classification techniques that were popularly used for disease identification in plants include k-nearest neighbour, support vector machine, fisher linear discriminant, artificial neural network, random forest and so on. As we all know that the disease recognition rates of the classical approaches rely heavily on the lesion segmentation and hand-designed features by various algorithms, such as seven invariant moments, Gabor transform, global–local singular value, and sparse representation, *etc*. However, the artificially-designed features require expensive works and expert knowledge, which have a certain subjectivity. Mainly, it is not easy to determine which features are optimal and robust for disease identification from the many extracted features. Besides, under the complex background conditions, most methods fail to effectively segment the leaf and corresponding lesion image from its background, which will lead to unreliable disease recognition results. Thus, the automatic recognition of plant disease images is still a challenging task due to the complexity of diseased leaf images. More recently, deep learning techniques, particularly convolutional neural networks, are quickly becoming the preferred methods to overcome some challenges.

Convolutional Neural Network

Convolutional Neural Network (CNN) is the most popular classifier for image recognition in both large and small scale problems. It has shown outstanding ability in image processing and classification. For example, their trained model achieves an accuracy of 99.35% on a held-out test set. Introduced a system based on CNN to recognize cucumber leaf disease; it realizes an accuracy of 94.9%, *etc*. Although very good results have been reported in the literature, investigations so far have used image databases with limited diversity. The most photographic materials include images solely in experimental setups, not in real field wild scenarios. Indeed, images captured in cultivation field conditions include a wide diversity of background and an extensive variety of symptom characteristics. Additionally, there are a vast number of parameters needed to be trained for CNN and its variants, while training these CNN architectures also requires multiple labelled samples and substantial computer resources from scratch to assess their performance. Collecting a large labelled dataset is undoubtedly a challenging task. Despite the limitations, the previous investigations have successfully demonstrated the potential of deep learning algorithms. Particularly, the deep transfer learning, which alleviates the problem faced by classical deep learning methods, *i.e*. the solutions consisting of using a pre-trained network where only the parameters of the last classification levels need to be inferred from scratch; is naturally employed in the practical application.

In this work, we study the transfer learning for the deep CNNs with the aim of enhancing the learning ability of tiny lesion symptoms along with decreasing the computational complexity.

The proposed approach is generally composed of two parts: The first part is the pre-trained module, which is used as a basic feature extractor; the other is an auxiliary structure that utilizes multi-scale feature maps for detection. Then, the convolutional layer is followed by two Inception modules, which are used to extract the multi-scale features of images input from the previous layer, and the fully connected layers are replaced by a global pooling layer to conduct the dimension reduction of feature maps. After that, a fully-connected softmax layer with a practical number of categories was added as the top layer of the modified networks.