Deep Convolutional Neural Networks

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The effectiveness of Convolutional Neural Networks in image recognition motivates the researchers to extend its applications in the field of agriculture for recognition of plant species, yield management, weed detection, soil, and water management, fruit counting, diseases, and pest detection, evaluating the nutrient status of plants, and much more. The availability of voluminous research works in applying deep learning models in agriculture leads to difficulty in selecting a suitable model according to the type of dataset and experimental environment. In this manuscript, the authors present a survey of the existing literature in applying deep Convolutional Neural Networks to predict plant diseases from leaf images.

Keywords: convolutional neural networks ; deep learning ; agriculture ; leaf ; disease ; survey

1. Introduction

There is an exponential increase in population around the globe. As per the report published in [1], the population is expected to reach 8.5 billion by 2030. Thus, there is a solid requirement to maximize the production of the agriculture industry for fulfilling the needs of the increasing population. The growth of bacteria, viruses, fungi, nematodes, and other microorganisms is increasing due to weather conditions such as temperature, humidity, and precipitation. Plants become more prone to diseases due to a large number of pathogens in their surroundings. Attacks of pests and diseases are significant causes of the reduction in crop production. Precise prediction of plant diseases well in time helps to apply suitable prevention and protection measures. Hence, it helps improve the yield quality and increase crop productivity.

Diseases in plants are detected by various symptoms such as lesions, changes in color, damaged leaf, damage in the stem, abnormal growth of stem, leaf, bud, flower and/or root, etc. In addition, leaves show symptoms such as spots, dryness, pre-mature falls, etc., as an indicator of disease [2]. Analyzing these observable symptoms is an effective way to detect plant diseases. The traditional disease detection approach is a visual examination of a plant by a trained or experienced person(s). However, the approach requires sound knowledge and expertise in the field of disease detection. Moreover, it can result in erroneous predictions due to visual illusions and biased decisions [3]. Thus, the approach is not a practical solution for large agricultural land.

Due to the availability of a plethora of research works in applying machine learning and deep learning models for predicting plant diseases, it becomes difficult for researchers to select an effective model according to the dataset, parameters, hardware configuration, and experimental conditions. Thus, there is a demand for a comprehensive survey of the existing literature that can assist the researchers in identifying a suitable model for data pre-processing, prediction, and classification of plant diseases. Therefore, the authors present an extensive survey of the pre-processing techniques, Deep Convolutional Neural Network (DCNN) architectures, DCNN frameworks, and Optimization techniques in this manuscript. In addition, the manuscript highlights the advantages, drawbacks, and applications of the deep learning models developed in the field of identification and classification of plant leaf diseases.

2. Comparative Analysis

Liu et al. presented the review of deep learning models employed for plant pest and disease prediction [10]. They highlighted the challenges in applying the deep learning models in plant disease prediction and highlighted the possible solutions for the identified challenges.

Authors in [11] performed experiments on images of leaves of watermelon, orange, corn, grapes, cherry, and blueberry, with a dataset size of 54,306 images from the PlantVillage. They achieved an accuracy of 82% by applying VGG16 architecture, 98% accuracy by using Inception-V4, 99.6% by ResNet50, 99.6% by ResNet101, 99.7% by ResNet152, and 99.75% accuracy by using DenseNet121 CNN architecture.

There is a vital requirement of applying a suitable optimization technique to improve the effectiveness of a CNN model. The discussion in Section 3.5.1 , Section 3.5.2 , Section 3.5.3 , Section 3.5.4 and Section 3.5.5 gives a brief description of the most applied optimization techniques. The authors present a comparison of the most commonly used optimization techniques in **Table 1** .

Table 1. Advantages and disadvantages of various optimization techniques.

Name of Optimizer	Advantages	Disadvantages
BGD	**Easy to compute, implement and understand.**	**It requires large memory for calculating gradients on the whole dataset. It takes more time to converge to minima as weights are changed after calculating the gradient on the whole dataset. May trap to local minima.**
SGD	**Easy to implement. Efficient in dealing with large-scale datasets. It converges faster than batch gradient descent by frequently performing updates. It requires less memory as there is no need to store values of loss functions.**	**SGD requires a large number of hyper-parameters and iterations. Therefore, it is sensitive to feature scaling. It may shoot even after achieving global minima.**
AdaGrad	**Learning rate changes for each training parameter. Not required to tune the learning rate manually. It is suitable for dealing with sparse data.**	**The need to calculate the second-order derivative makes it expensive in terms of computation. The learning rate is constantly decreasing, which results in slow training.**
RMSProp	**A robust optimizer has pseudo curvature information. It can deal with stochastic objectives very nicely, making it applicable to min-batch learning.**	**The learning rate is still handcrafted.**
Adam	**Adam is very fast and converges rapidly. It resolves the vanishing learning rate problem encountered in AdaGrad.**	**Costly computationally.**

Developments in Artificial Intelligence provide various tools and platforms to apply deep learning in different application areas. A brief description of commonly used frameworks is given in Section 3.6.1 , Section 3.6.2 , Section 3.6.3 , Section 3.6.4 , Section 3.6.5 , Section 3.6.6 , Section 3.6.7 , Section 3.6.8 and Section 3.6.9 .

3. Current Insights on Deep Convolutional Neural Networks

A survey of the existing literature in identifying and classifying plant leaf diseases using Deep Convolutional Neural Networks (DCNN). The entry identified the closely related research articles for presenting the comparative analysis of different DCNN architectures. The survey focuses on the study of plant diseases, datasets used, size of the datasets, image pre-processing techniques, CNN architectures, CNN frameworks, performance metrics, and experimental results of different models applied to identify and classify plant leaf diseases.

For the classification of plant leaf diseases, the researchers applied traditional techniques of augmentation such as rotation [12][13], flipping, scaling, cropping, translation [14], and adding Gaussian noise [15]. They achieved satisfactory outputs using the above-stated techniques. Thus, the literature has observed the minimum use of deep learning augmentation techniques, such as Generative Adversarial Networks, Neural Style Transfer, etc.

The performance of DCNN models is directly proportional to the amount and accuracy of the labeled data used for training. If there is a low availability of data for training the model, then fine-tuned pre-trained models can give better results than the models trained from scratch.

There is also scope in the automatic estimation of the severity of plant diseases which may prove helpful to farmers in deciding what measures they need to take for the culmination of a disease.

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