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DEEP CNN MODELS IN PLANT DISEASE IDENTIFICATION

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Abstract

Deep learning, comprising of modern techniques to process images and analyze data with good results in terms of accuracy, is outperforming existing commonly used techniques. Like in many other fields, deep learning has entered the field of Agriculture also and been applied to various aspects of farming including plant disease detection which contributes significantly to quality and quantity of crop production. In this paper different research efforts employing different models of deep learning in plant disease detection are presented. Presented work has tried to identify the features of different deep learning models and their comparative study. In this paper, a concise summary of different works employing the application of Deep convolution network (CNN) in various research works related to plant disease identification, have been presented.

I. Introduction

Major production and economic losses in the agricultural industry throughout the world are due to diseases in plants. For sustainable agriculture, monitoring of health of plants and early identification of disease

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is very crucial. Damage created by plant diseases can adversely affect the production both in terms of quality and quantity. To ensure quality and quantity of crops it is important to protect plants from diseases that affect plant leaves, stem, and fruits. Classification of plant diseases can be a complex task as the protection and detection strategy depends hugely on the academic knowledge and experiences, intuitions of farmers, agricultural experts and scientists. Continuous monitoring of crops with symptoms of diseases was required which was difficult as well as time consuming and consequently led to development of automated systems to support this. Different studies (Akhtar, A. et al., Al Hiary, H. et al., Dandawate, Y. et al., Mokhtar, U. et al.) are there making use of machine learning and image processing of the images taken from crops to build image classifiers. These classifiers were based on features crafted and designed by experts and then classifiers were trained with manually labelled images. The entire process was time consuming and involved dependencies on human experts because of which limited dataset was prepared for training and testing the classifiers. Use of small dataset labelled manually proved out to be limiting factor in machine learning and consequently over fitting was observed. Since last few years Deep Learning (DL) is getting more popular in different aspects of farming including plant disease detection. The major advantage of applying deep learning is the direct exploitation of images without any human intervention in crafting features. In this fully automated way, working on a huge dataset of images, more accurate classifiers are produced.

II. Deep Learning and Plant Disease Detection

In recent years, many image classifications work in different fields including agriculture and plant disease detection are employing Convolution Neural Network and are showing great results in terms of classification accuracy. The first CNN was introduced in 1980. It is a complex feed forward neural network inspired by natural image recognition by humans. Primarily CNNs are applied in image identification and classification due to high accuracy. Convolution is an operation in mathematics which operates on two functions to produce another function. In fact, a CNN reduces the images into simple forms without any significant feature loss to make images easier to process. A CNN has multiple layers of artificial neurons where a neuron is a mathematical function that finds the weighted sum of multiple inputs and outputs gives back an activation value. So, when an image is given in a CNN, each layer produces many activation functions which are further passed on to next layer. In CNN three types of layers are there-convolutional, pooling and fully connected. Generally, first layer extracts few basic features in image like edges and then output is given to next layer to find somewhat more complex features like corners. In this way we go deeper into the NN to detect more complex features like object. The activation map received as output of final layer; confidence scores are generated by classification layer to know the class of the image. In order to reduce the computational power needed for data processing, dimensions are reduced. It is the pooling layer which is responsible for decreasing the spacial size of the convoluted features. CNNs constitutes powerful techniques for modelling problems complex in nature and specifically involving pattern recognition in large amount of data like pattern recognition in images of plant leaves. Plant disease detection is done by identifying the spots on the leaves of affected plants. The overview of deep learning system is presented in Figure 1. The complete system consisted of few steps. Preparation of dataset is done which includes pre-processing of images, their labelling in first step. This is followed by splitting of dataset into training and test data. Then deep CNN model is trained with training dataset for classification and identification of plant disease.

Image collection and pre-processing

First, data set is collected and processed. Pre-processing involves resizing, reshaping, and converting images into array form. Collection is an important stage as deep models need huge datasets to avoid over fitting. Labelling involves image annotation. It is an expensive and time-consuming process while DL models like CNN needs big, labelled data. In this context, data augmentation helps in increasing labelled examples and in producing variations in training set. Augmentation involves both geometric transformations like rotations, flipping, resizing etc. and intensity transformation like brightness, color, noise etc. To normalize the images in the data set pre-processing techniques are used.

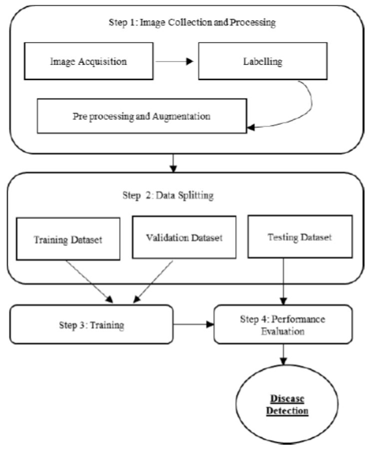

Figure 1. Overview of Deep Learning System.

Data Splitting

The next step in the process is to divide the collected data into training, validation, and testing datasets. Training dataset consists of samples of data used to fit the deep model and validation dataset is created to evaluate fit model on training dataset. Purpose of validation dataset is to provide an unbiased evaluation while tuning model hyper parameters. Sample of data used to evaluate final model fit on training data set is test dataset. It is used after the model has completely been trained with the help of training and validation datasets. Data split ratio of these datasets depends upon the model to be trained.

Training of DL Architectures/ Models

Majority of times DL and particularly CNN models are trained using algorithm of back propagation. This stage may consist of two phases – Pre training and fine tuning. Pre-training involves training deep CNN on any other large dataset (ImageNet) prior to the original dataset. It prepares CNN and helps in identification of lacking for plant disease detection. Fine tuning is a transfer learning method which is an optimization for improved performance.

Specifically, in the field of plant disease detection deep learning techniques has started to be used in last couple of years only. Work done by Kawasaki, Y. [13] utilized the CNN to differentiate infected cucumber leaves from healthy leaves. Research made use of 800 images of cucumber leaves. Out of these 800, 300 were infected with melon yellow spot virus, 200 with zuccchini yellow mosaic and res 300 were healthy ones without any disease. To increase the dataset, rotation transformation was applied. The proposed architecture consisted of 3 convolution layers, pooling layers and local contrast normalisation layers. It was using Rectified Linear Unit as activation function and achieved 94.9% accuracy.

In another work done by Sladojevic, S et al. [29] deep CNN was applied on 13 classes of plant diseases. Apart from this one class for healthy leaves and one more class of background images to distinguish leaves from background were also considered. In total 4483 different images were used and later on to reduce the over-fitting in training stage this dataset was pre-processed and augmented to make it of around 40,000 images out of which 30880 were used for training purpose and 2589 for validation. Researchers proposed transfer learning using CaffeNet architecture which is modified version of AlexNet. The overall accuracy of the architecture was 96.3% with fine tuning and 95.8% without it. The CNN was trained with both fine tuning as well as without fine tuning process.

Researchers in their work by Mohanty [18] made use of plant village dataset which consisted of 38 labelled classes with 26 diseases found in 14 species of crop. To ensure variety in his work and to achieve better results dataset was used in both coloured and grey scale mode. Even the multiple distributions of training and test data were applied to measure the performance of CNN. Architectures used for classification were AlexNet and GoogLeNet. Both the training strategies were used, scratch and transfer learning. From all the configurations applied the highest accuracy achieved was 99.34% through transfer learning of GoogLeNet on coloured images with 80-20 training-test distribution. The major limitation of the work was that the available images were captured in controlled environment.

A CNN was proposed by Nachtigall et al. [20] for detecting nutritional deficiencies and damages from apple leaves. To build the classifier AlexNet CNN architecture was used on a dataset of 1450 images. Total 5 classes were used, 2 for malnutrition, 1 for damage because of herbicides and 2 for damages caused by diseases. Each class consisted of 290 images. 192 were used for training, 83 for validation and 15 for testing in each class.

Researchers compare shallow methods against deep CNN. CNN took a lead with accuracy of 97.3% as compared to human experts where accuracy was 96%.

Seven different type of diseases were considered in a work done by Fujita, E et al. [9] for classification of cucumber diseases along with healthy class. Researchers made use of two datasets. One with 7320 images clicked under controlled environment and good condition. The second dataset had 7520 images captured with both kinds of conditions. Augmentation techniques of mirroring and rotations were used to populate dataset. The accuracy of the proposed work was found to be 82.3% which consisted of 4 convolutional layers alternated with max-pooling layers and local response normalization function with parameters from AlexNet architecture.

CNN was applied in another work (Brahimi, M, [3]) for classification of nine tomato diseases from 14828 images. The standard architectures AlexNet and GoogLeNet were trained with and without fine tuning. Fine tuning improved the accuracy in GoogLeNet from 97.7 70 99.1% and in AlexNet from 97.3 to 98.6%. Accuracies of CNN models were compared with SVM and Random Forest where the former technique has 94.53% of accuracy and later had 95.46%.

Another work was observed by DeChant, C [6] also where blight lesions were classified from the images of maize plants leaf. Dataset consisted of 1028 images of infected leaves while 768 images of healthy leaves. Training-Validation- Testing dataset ratio was 70-15-15. Overall training was done in three stages. In first stage, multiple CNN models were trained to identify lesions in small parts of maize leaf images. In next stage these models were used to produce heat map depicting the probability of infection in every image. In third and last stage, the generated map was used to classify images. The system achieved the accuracy of 96.7%.

Researchers Lu, Y et al. [16] used AlexNet CNN architecture for the classification of diseases in rice. They captured 500 images in rice fields to build their own dataset for training and validation purpose. Under 10 fold cross validation the deep model was 95.4% accurate while SVM achieved an accuracy of 91%, back propagation 92% and Particle Swarm Optimization 88%.

III. Models of Deep Learning Used in Different Works to Identify Diseases in Plants

This section presents the various state-of-the-art deep learning architectures used for identification, segmentation and classification of diseases in plants. Deep learning boom was started with AlexNet in 2012. Here common and popular architectures of CNN used in plant disease detection are discussed to elaborate their functionality for performing an image identification task. AlexNet is a GPU implemented CNN model which at time of its introduction in 2012 triggered a deep learning explosion because of high accuracy levels achieved due to its use.

Different DL models are implemented in plant disease detection with or without visualization techniques. In work by Sibiya, M [28] histograms techniques were used to prove the effectiveness of the CNN model used in classification of diseases in maize plants. To provide training to CNN model Neuroph was used to identify and classify maize leaf diseases (common rust, grey leaf spot and corn leaf blight) from the images captured through camera of smart phone. Overall accuracy achieved is 92.8%. In order to identify tomato leaf disease detection AlexNet, ResNet and GoogLeNet were implemented.by Zhang, K [31] on performance scales ResNet was proved out to be best among all of them with 97.28% accuracy. Here also Neuroph framework was used to work. In another work by Ferentinos, K.P [8] total 5 CNN models were used to identify diseases in banana leaves namely AlexNet, AlexNetOWTbn, Overfeat, GoogLeNet and VGG and VGA was found to be most suitable. Few more DL models GoogLeNet, ResNet 50, ResNet 101, Inception v3, InceptionResNetv2 and SqueezeNet are used in (2019) by M.; Hanbay along with 3 classifiers SVM, Extreme Learning Machine and K-Nearest Neighbor to plant diseases. Performance metrics used were specificity, sensitivity and F1 score and ResNet-50 with SVM classifier was found to outperform. In (Ramcharan, A, [23]) use of new DL model Inception v3 was observed. AlexNet and VGG 16 deep learning architecture were used to classify 6 tomato plant diseases in (Rangarajan, A.K, [23]). In all the approaches discusses here, no visualization techniques were used to spot the symptoms.

Different works to be discussed after this are making use of techniques of visualization to better understanding of the plant diseases. In work by Sladojevic CaffeNet CNN model was used to detect 13 different plant diseases with accuracy of 96.3%. To indicate the spots of diseases many filters were used. In work by Brahimi, M a new DL model was introduced with a proposal of a novel technique of visualization. In another work by Fuentes, A (2017) SSD, RFCN and Faster RCNN detectors were used with many popular DL architectures. With the comparative study it was concluded that ResNet 50 with RFCN detector was giving best results. To spot the disease for identification a bounding box was drawn. A banana leaf disease and pest detection in work by Selvaraj, M. G. [27] was performed with three CNN model namely Inception V2, MobileNet V1 and ResNet 50 and two detectors Faster RCNN and SSD. According to DeChant, C et al. [6] different combinations of CNN architecture were applied and presented heat map as input to the images of plants with disease. To evaluate the performance ROC curve was used. In work by Brahimi, M [3] tomato plant disease detection was done using AlexNet and GoogLeNet architectures. As per the result of comparison done GoogLeNet performed better. Apart from this work also introduced the technique of occlusion to identify the regions of diseases. To visualize the features and detect diseases in wheat plants VGG-FCN and VGG-CNN models were implemented in work by Lu, J [15] Work done by researchers Lin, K et al. [14] made use of semantic segmentation approach.

Work by Ferentinos, K. P [7] trained a CNN model to identify plant diseases from image dataset. In this proposed research work, an accuracy of 97% is achieved. The CNN architectures used in the proposed framework include AlexNet, AlexNetOWTBn, and GoogLeNet. A comprehensive review of various deep learning algorithms was presented along with their advantages/disadvantages and their optimization techniques. A comparison has also been made for these techniques about the related work by Golhani, K et al. [10]. Researchers Sardogan, M et al. [26] proposed a model that is a combination of convolution neural network and linear vector quantization algorithm. The dataset included 500 images of tomato leaves.

IV. Features of Common Deep Learning Methods

Convolutional Neural Network works on images as input. To these provided inputs, it give learnable weights and biases to different identifiable objects in image. The basic architecture of CNN is inspired by the connectivity pattern of the Neurons in human brain. Receptive field is the restricted area of visual field where individual neuron give response to stimuli. The complete visual area is covered by collection of these fields overlap. Table 1 lists the commonly used deep learning models used in different works as discussed in above sections along with their features. The models have been presented in table according to their evolution starting effectively from 2012 to recent years.

Table I. Deep Learning Models and their Features.

Year	DL Model/ Architecture	Key Features
1998	LeNet	first successful application of convolutional neural network to process high resolution needed more convolutional layers requires high computing resources
2012	AlexNet	similar architecture as LeNet more filter per layer with stacked convolutionn layer Number of parameters 60 millionconsisted of covolutions, max pooling, dropout, augmentation, ReLU activations
2013	ZFNet	reduced error rate drastically Number of parameters 42.6 million reduced weigths as compared to AlexNet model
2014	GoogLeNet/ Inception	inspired by LeNet with performance close to human level used several small convlutions, 22 layer deep CNN, reduced number of parameters (4 milion) implememted element which is dubbed an inception module used batch normalization, image distortion and RMSprop
2014	VGGNet	uniform architecture consisting of 16 convolutional layers preferred choice for

		extracting feature 138 million parameters making it difficult to handle
2015	ResNet	skip connection architecture and heavy batch normalization able to train a neural network with 152 layers less complex than VGGNet 25.5 million parameters
2016	SqueezNet	consisted of 18 deep layers reduced input channels, large activation maps of convolutional layer faster and smaller than AlexNet with similar accuracy 1.25 millions of parameters
2017	DenseNet	Dense connection between the layers reduced number of prameters with better accuracy 7.1 millions of parameters
2018	PNASNet	Progressive Neural Architecture Search use reinforcement learning and evolutionary algorithms more efficient and faster
2019	EfficientNet	More layers to capture complex features 7.8 million parameters

V. Conclusions and Future Work

The presented paper explained different deep learning models and architectures used for the detection of plant diseases. Common deep CNN architectures are AlexNet, GoogLeNet, Inception, ResNet etc. In last five six years DL approaches have widely been used in many works. After analyzing the utilization of DL architecture in different works it was observed that still certain research gaps are present. Majority of work done is on dataset available in PlantVillage. Majority of images available here are under controlled environment in laboratory conditions with simple background. Inclusion of images with field environment is required. With the passage of time severity of plant diseases changes so DL models should be modified accordingly to improve the detection and classification throughout the complete life cycle of plants.

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