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Mango Leaf Diseases Identification Using Convolutional Neural Network

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Abstract

The identification of plant diseases plays a vital role in taking disease control measures in order to improve the quality and quantity of crop yield. Automation of plant diseases is very much beneficial as it reduces the monitoring work in large farms. Leaves being the food source for plants, the early and accurate detection of leaf diseases is important. This work includes a deep learning based approach that automates the identification of leaf diseases in Mango plant species. Five different leaf diseases such as Anthracnose, Alternaria leaf spots, Leaf Gall, Leaf webber, Leaf burn of Mango has been identified in a dataset consisting of 1200 images of diseased and healthy mango leaves. The proposed CNN model achieves an accuracy of 96.67% for identifying the leaf diseases in mango plant thereby showing the feasibility of its usage in real time applications.
Keywords: Deep learning, Convolutional Neural Network, Mango leaf diseases.

1 Introduction

Mango also called as The King of Fruits is one of the important fruit crops cultivated in different countries around the world. India produces about 40% of the global mango production and ranks first among the worlds mango producing countries. It is estimated that, pests and diseases destroy approximately 3040% of the crop yield [1]. The common diseases of mango plant includes gall infestation, webbers attack, mango malformation, stem miner, anthracnose, alternaria leaf spots etc. Such diseases are caused by pathogens like bacteria, virus, fungi, parasites etc, and even unfavourable environmental conditions. Disease in leaf affects the photosynthesis process thereby leading to plant death. The symptoms and the affected leaf area determine the type of disease. In earlier days, identification of plant diseases was usually carried out by frequent monitoring of plants by farming experts. In case of small farms it was possible to identify the diseases easily and take immediate preventive on control measures. But in the case of large farms, it is time consuming and expensive. Therefore looking for an automatic, accurate, fast and less expensive technology for plant disease identification is of great importance. Image processing and machine learning are most popular and widely used techniques adopted for plant leaf disease detection and classification. Deep learning using Neural Networks is a part of the wider family of machine learning. It has spread its arms in various fields providing a huge variety of applications. The development of such computer technology can help farmers to monitor and control diseases in plants.

2 RELATED WORKS

Leaf disease detection has been a long research topic for the past few decades. In order to improve the recognition rate of disease diagnosis, researchers have studied many techniques using machine learning and pattern recognition. The techniques include machine learning techniques such as Convolutional Neural Network [2], Artificial Neural Network [3], Back Propagation Neural Network [4], Support Vector Machine [5] and other image processing methods [6,7]. In the above techniques, Convolutional Neural Network performs both feature extraction and classification itself. Others methods use Color Co-occurrence matrix [8], Angle Code Histogram [4], Zooming algorithm [9], Canny edge detector [6] and various other algorithms for feature extraction. Research works have been carried out to classify a single disease in multiple plants varieties or multiple diseases in a single plant species. These advanced techniques are applied to many crops such as rice [2], wheat [10], maize [11], cotton [12]. Also CNN requires less or no preprocessing of images when compared to other techniques. Recently, several studies on automated diagnosis of plant diseases have been conducted using deep learning techniques. Yang Lu et al. proposed a method for detection and classification of unhealthy leaf images of rice plant using Deep Convolutional Neural Network. A dataset of 500 natural images of diseased and healthy rice leaves and stems captured from rice experimental field was used. CNNs are trained to identify 10 common rice diseases under the 10-fold cross-validation strategy. Also, since color images are used, the stationary property does not hold across color channels, therefore the images are rescaled in [0, 1] and Principal Component Analysis and Whitening are applied to get training features and testing features [2]. Alvaro Fuentes et al. [13] proposed a deep learning based detection mechanism for real time leaf disease and pest recognition in tomato plant. Three different detectors such as Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD) are used to recognize 9 different tomato diseases using a dataset of 5000 images. Additionally data annotation and data augmentation are performed to reduce false positives and also increase the accuracy. Mohanty [14] et al. proposed a leaf disease detection model based on deep Convolutional Neural Network. This work was able to classify 38 classes consisting of 14 crop species and 26 disease varieties using a dataset of 54,306 images form Plant Village dataset. In this work, an automated mango leaf disease identification method based on deep Convolutional Neural Network is proposed to achieve fast and accurate recognition results by using ReLU activation function and batch normalization. This work aims at identifying five different Mango leaf diseases such as Anthracnose, Alternaria leaf spots, leaf gall, leaf burn and leaf webber. The CNN performs automated feature extraction from the raw inputs in an analytical way. The classification is based on selecting the features with highest probability values. The remaining of this paper is organized as follows. Section 3 describes the architecture of the CNN model. Section 4 describes the implementation of mango leaf disease identification using the proposed CNN model, followed by the results of this work in Section 5. Section 6 deals with the conclusion.

3 ARCHITECTURE OF DEEP CONVOLUTIONAL NEURAL NETWORK

A CNN consists of an input layer and an output layer, as well as multiple hidden layers between them. The hidden layers basically consists of the convolution layer, pooling layer, Rectified Linear Unit, dropout Layer and normalization layers. In the case of image classification, the input is an image and the output is the class name also called label. Inspired by various pre-trained Convolutional Neural Network architectures such as VGG-16, VGG-19, Alexnet, a deep CNN architecture with three hidden layers has been proposed for this work. There is no precise rule in organizing the structure of the individual layer.

3.1 Input Layer

The image can be given as input directly to the CNN model. The size of the image is denoted as [height width number of color channels]. For color image the number of color channels corresponds to 3 and for the grayscale image it is 1. Data augmentation can be done before passing the images to the CNN model. Since neural networks and deep learning models requires large amount of data, the dataset is increased by generation of artificial data through expansion of original dataset. The images are augmented by applying different transformations that include rotations, zooming, cropping, transpose and skewing while preserving the label of the image.

3.2 Convolutional Layer

The prime operation of convolutional layer is convolution operation. The first layer in a CNN is always a convolutional layer for which the input is an image, in case of first network layer or feature map from the previous layer. The input is convolved with the filters, called kernels in order to produce the output feature maps. The convolution output can be denoted as,

$$x_j^l = f\left(\sum_{i\in M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right)$$

where, x_j represents the set of output feature maps, M_j represents the set of input maps, K_{ij} represents the kernel for convolution, b_j represents the bias term. The size of the output feature map is given by,

$$O = \frac{W-K+2P}{S} + 1 \qquad (3.2)$$

where, O is the output height/length, W is the input height/length, K is the filter size, P is the padding, and S is the stride. In order to preserve the size of the output, padding of zeros can be employed on the edges of the input. The amount of padding, P can be determined as follows,

$$P = \frac{K-1}{2} \qquad (3.3)$$

where, K is the filter size.

3.3 ReLU Layer

The Rectified Linear Unit layer also called as the activation layer is used to introduce some non-linearity to the system, since it performs linear operations during the convolution process. So, it is introduced after every convolution layer. This layer simply changes all the negative activation values to 0. The ReLU layer performs a thresholding operation to each element given by,
f(x) = max(0,x)
This layer plays a significant role in alleviating the vanishing gradient problem and helps to train the system faster. The ReLU suits well for multiclass classification. For binary classification, the sigmoid function can be used. instead of ReLU.

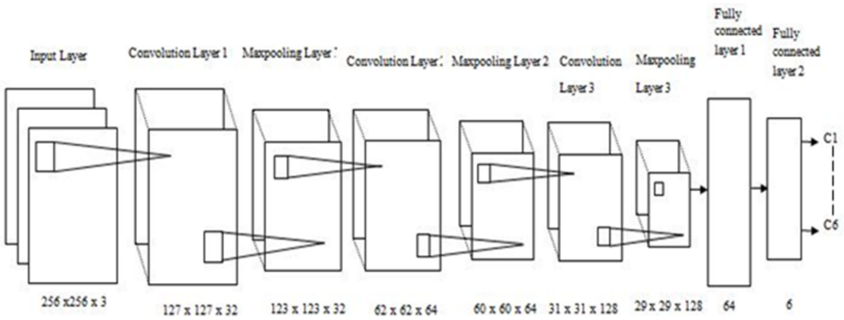

Fig 1: CNN Architecture

3.4 Max-Pooling Layer

In this layer, the input is divided into multiple non-overlapping blocks and outputs the maximum among the elements in each block to form an output of reduced size while preserving the important information in the input. It is also capable of controlling the over fitting problem. There is no learning process in this layer.

3.5 Dropout Layer

The basic idea of the dropout layer is that, the input elements with a certain probability are deactivated or dropped out such that the individual neurons are able to learn the features that are less dependent on its surroundings. This process takes place only during the training phase.

3.6 Batch Normalization Layer

The Batch Normalization layer is usually present between the convolution layer and the ReLU layer. It increases the training speed and reduces the sensitivity of network initialization. In this layer the activations of each channel are normalized by subtracting the mini-batch mean and dividing by the mini-batch standard deviation. This is followed by shifting the input by an offset β and then scaling it by a factor γ. These two parameters are updated during the training phase. The batch normalized output, y_i is given by,

$$y_i = BN_{\gamma,\beta}(x_i) \equiv \gamma\hat{x}_i + B$$

where,$\hat{x}_i$ is the normalization of activation xi which is given by equation (3.6).

$$\hat{x}_i = \frac{x_i + \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}}$$

where, ε is a constant, μ_B is the mini-batch mean and σ_B^2 is the mini-batch variance given by,

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_B)^2$$

where, m is the mini-batch size. In this way network training can be made faster by making the optimization problem easier.

3.7 Fully Connected Layer

In the fully connected layer all the neurons of this layer are connected to all the neurons in the previous layer, thereby combining all the features learned by the previous layer to facilitate classification. This layer produces an N-dimensional vector at the output, where N is the number of classes.

3.8 Output Layer

The output layer consists of the softmax layer followed by the classification layer. The softmax layer outputs a probability distribution based on which, the network model classifies an instance as a class that has the maximum probability value. The Softmax function also called Normalized Exponential is given by equation (3.9).

$$P(c_r|x,\theta) = \frac{P(x,\theta|c_r)P(c_r)}{\sum_{j=1}^{k} P(x,\theta|c_j)P(c_j)}$$

where, $\leq P(c_r|x,\theta) \leq 1$ and $\sum_{j=1}^{k} P(c_j|x,\theta) = 1$ $P(x,\theta|c_r)$ is the conditional probability of an instance given class r and is the class priori probability. The equation (3.9) can also be written as follows,

$$P(c_r|x,\theta) = \frac{\exp(a_r(x,\theta))}{\sum_{j=1}^{k} \exp(a_j(x,\theta))}$$

where, $a_r = \ln(P(x,\theta|c_r)P(c_r))$

4 LEAF DISEASE IDENTIFICATION USING CNN

Mango leaf diseases image database is created by acquiring images under challenging conditions such as illumination, size, pose and orientation, using a digital camera of resolution 4608 x 3456. It consists of 1200 images of both diseased and healthy leaves. The diseases include Anthracnose, Alternaria leaf spot, leaf gall, leaf webber, leaf burn of mango plant. In order to reduce the computational time complexity, the images are resized from the size 4608 x 3456 to 256 x 256. The proposed CNN architecture consists of an image input layer followed by three hidden layers and then the output layer. The layer implementation is represented in Table 1.

Table 1: Layer Implementation of the CNN model

Layer	Filter Size	Output Size
Input		256 x 256 x 3
Convolutional Layer 1	11	127 x 127 x 32
Maxpooling Layer 1	5	123 x 123 x 32
Convolutional Layer 2	7	62 x 62 x 64
Maxpooling Layer 2	3	60 x 60 x 64
Convolutional Layer 3	5	31 x 31 x 128
Maxpooling Layer 3	3	29 x 29 x 128
Output		6 x 1

The leaf images of size 256x256x3 are given as input to the input layer. Data augmentation is performed in order to increase the dataset by generating artificial data. The images are then passed through the hidden layers. Each hidden layer consists of a convolutional layer, batch normalization layer, Rectified Linear Unit followed by the max pooling layer. Feature extraction is performed using convolutional and pooling layers, whereas classification is performed by the fully connected layer. Each convolutional layer and pooling layer consists of different number of filters, of varying size. The three convolution layers consists of 32, 64, 128 filters of size 11x11, 7x7, 5x5 respectively with stride 2 and padding based on the formula (3.3). The batch normalization layer and the ReLU layer increase the training process and network performance. The three max pooling layers consists of 5x5, 3x3 and 3x3 filters respectively with stride 1 and padding, P=1 for maxpooling layer 1 and P=0 for maxpooling layers 2 and 3. Then 50% dropout is employed to deactivate the least learned features. The features learnt by the convolutional and pooling layers are then classified by using two fully connected layers of size 64 and 6 respectively. The size of the second fully connected layer is equal to the number of classes. It specifies the probability distribution for each class. Steepest Gradient Descent algorithm is used to train the proposed CNN model with 50 % of the images in each class. The remaining 50% images are tested. Since CNN is a supervised learning network, the labels are also trained along with the images. The plot for the network training progress is shown in Figure 2.

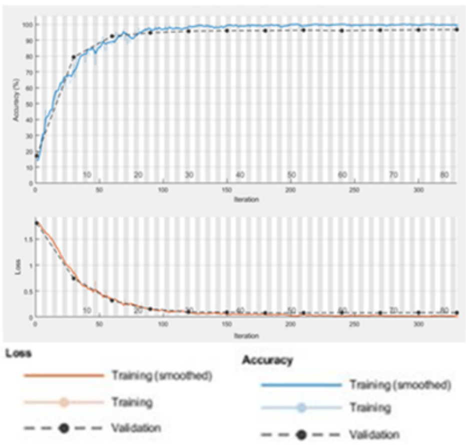

Fig 2: Plot for Training Progress

The Training progress plot shows the increase in training accuracy

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and simultaneous decrease in loss as the number of iterations increases during the training and validation processes. The loss is the summation of error made for each sample in the training and validation sets. Lower the loss, better is the model and recognition results.

5 RESULTS

The proposed CNN model was trained with 100 images per class totally accounting for 600 training images. The remaining 600 images constituting of 100 images per class was tested. The testing accuracy resulted in 96.67%. The confusion matrix is shown in Table 2

Table 2: Confusion Matrix

Class	C1	C2	C3	C4	C5	C6
C1	86	9	5	0	0	0
C2	0	94	6	0	0	0
C3	3	0	100	2	2	0
C4	0	0	0	100	0	3
C5	0	0	0	0	100	0
C6	0	2	3	2	0	100

The classes C1 to C6 is listed in the Table 3.

Table 3: List of Classes

Class	Label Name
C1	Healthy leaf
C2	Anthracnose
C3	Leaf gall
C4	Leaf burn
C5	Alternaria leaf spot
C6	Leaf webber

Among the 6 classes, classes 3 to 6 have produced 100 % classification results since those diseases have distinctive appearance and features when compared to other classes.

6 CONCLUSION

The proposed CNN based leaf disease identification model is capable of classifying 5 different diseases in mango leaves from the healthy one. Since CNN does not require any tedious preprocessing of input images and hand crafted features, faster convergence rate and good training performance, it is preferred for many applications rather than the conventional algorithms. The classification accuracy can be further increased by providing more images in the dataset and tuning the parameters of the CNN model. But obtaining the optimal parameters for a CNN model is still a research challenge.

References

[1] http://www.sciencedirect.com/topics/agricultural-and-biological-sciences/plant-diseases.

[2] Yang Lu, Shujuan, Nianyin Zeng, Yurong Liu, Yong Zhang, (2017), Identification of Rice diseases using Deep Convolutional Neural Networks , Elsevier Journal on Neurocomputing.

[3] Elham Omrani, Benyamin Khoshnevisan, Shahaboddin Shamshirband, HadiShaboohi, Nor Badrul Anuar, Mohd Hairul nizam md nasir, (2014), Potential of redial basis function- based support vector regression for apple disease detection, Measurement, vol.55,pp:. 512-519.

[4] Kshitij Fulsoundar , Tushar Kadlag , Sanman Bhadale , Pratik Bharvirkar, (2014), Detection and classification of plant leaf diseases, International Journal of Engineering Research and General Science Volume 2, Issue 6.

[5] Shivaputra S.Panchal, Rutuja Sonar, (2016). Pomegranate Leaf Disease Detection Using Support Vector Machine, International Journal Of Engineering And Computer Science ISSN: 2319-7242 ,Volume 5 Issues 6.

[6] R.Preethi, S.Priyanka, U.Priyanka , A.Sheela, (2015), Efficient knowledge based system for leaf disease detection and classifi-

cation, International Journal of Advance Research In Science And Engineering, Vol. No.4, Special Issue (01).

[7] P.Revathi , M.Hema Latha, (2012), Classification Of Cotton Leaf Spot Diseases Using Image Processing Edge Detection Techniques International Journal of Applied Research ISBN, 169-173.

[8] S. Arivazhagan, R. Newlin Shebiah , S. Ananthi, S. Vishnu Varthini, (2013), Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features, CIGR Journal, Vol. 15, No.1 211.

[9] Santanu Phadikar, Jaya Sil, (2008), Rice Disease Identification Using Pattern Recognition Techniques, Proceedings Of 11th International Conference On Computer And Information Technology, 25-27.

[10] K. Khairnar, R. Dagade, (2014), Disease detection and diagnosis on plant using image processing - a review, Int. J. Comput. Appl. 108 (13), 3639.

[11] L.N. Zhang , B. Yang , (2014), Research on recognition of maize disease based on mo- bile internet and support vector machine technique, Trans. Tech. Publ. 108 (13) ,659662.

[12] Z. Shicha , M. Hanping , H. Bo , Z. Yancheng , (2007), Morphological feature extraction for cotton disease recognition by machine vision, Microcomput. Inf. 23 (4) ,290292 .

[13] Alvaro Fuentes, Sook Yoon, Sang Cheol Kim, Dong Sun Park, (2017), A Robust Deep-learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Detection. Sensors, 17(9): 2022.

[14] Mohanty S P, Hughes D, Salathe M, (2016), Using Deep-Learning for Image Base Plant Disease Detection., Front. Plant Sci.: 7:1419., 10.3389/fpls.2016.01419.