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Residual Neural Network (ResNet) Based Plant Leaf Disease Detection and Classification

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Abstract

Agriculture is the backbone of every country but the more types of Agriculture produces development requirements of today environment. So Ancient agriculture is an unpredictable one and also several problems are included in the traditional Agriculture. This paper introduces a dataset of plant leaf vein images from Rose Leaf, Cucumber Leaf. The Rose Leaf and cucumber leaf is a Dicot because it has a main vein with other veins branching off it. Then multiple instances of the dataset containing 64x64, 32x32, pixel single-channel center-focused images were created, and a new Residual Neural Network (ResNet) based model has applied on each of the instances for group identification. The same procedure is followed for plant leaf disease classification. The aim was to make use of only the vein patterns for the task. The experimental results show that despite the difficulties of recognizing patterns from small-scale images, it is likely to efficiently categorize plant leaf disease by properly deploying residual blocks in neural network models.

Keywords: Leaf vein, Plant Disease, Classification, Residual network, Residual Neural Network.

1. Introduction

Agriculture is considered as the primary source of food production and it is the basic foundation in the developing countries which creates opportunities to raise the country's economy [1]. Agriculture along with its associated sectors is unquestionably the largest livelihood provider in India. Around 70 percent of its rural households in India still depend primarily on agriculture for their livelihood, with 82 percent of farmers being small and marginal [2]. The number of plants is over extensive, with about lot of plant diseases all around the world. Therefore, it is inconceivable and impractical for a specialist, to be able to recognize and categorize all the diseases [3]. In summation, some plant diseases may have deep equivalency among each other, requiring much longer time and effort to categorize them. Hence, automatic plant identification is a growing and demanding problem that has acknowledged cumulative attention in recent years, particularly for identification based on leaf image analysis. The ultimate target of optimization, in this case, is to eliminate the use of human specialists handling huge estimated lists of plant species and to minimize classification time [4].

In recent times, in many exceptional appliances to machine learning, there is an inclination to replace the classical techniques with deep learning algorithms [5]. In deep learning methods, features are automatically extracted by the models, eliminating the need for handcrafted feature extraction. Moreover, classification outcomes are much improved than those earned with classical techniques [6]. Leaf shape is the most generally used feature for constructing an automated plant identification system. Other features than the shape, the leaf can supply some additional information, such as a vein structure, which is the key concept behind building the dataset [8].

Plant disease classification methods have been deployed by several researchers in recent years, which have accomplished great outcomes in the related fields [9]. Various characteristics such as aspect ratio (ratio between length and width of the leaf), the ratio of the parameter to the diameter of the leaf, and vein characteristics were used to categorize the leaf to identify specific plants diseases [10]. Deep learning was used for plant leaf disease classification using leaf vein morph metric [11].

2.Background study

A complex pattern recognition problem requires deeper neural networks. However, difficulties in training increase with network depth. Residual neural networks (ResNet) are capable of simplifying the complications introduced by the intense network depth [15]. For this reason, the ResNet -based method was developed for recognition purposes in this work. This research presents a leaf image dataset to identify dicotyledonous plants which are much familiar and can be easily collected from the surroundings. Much care was given to collecting and preprocessing the dataset.

Lee et al., [7] proposed a deep learning method was used to extract, and learn leaf features for plant classification. Grinblat et al., [12] have shown in his work how automatic classification of legumes can be done using leaf vein image features. Walls [14] utilized phylogenetic, standard ANOVA along with regression and introduced novel universal phylogenetic inspection on Angiospermae vein morphology, including characteristics of leaf functions. Larese et al., [13] proposed a scheme for differentiating legumes solely depending upon the leaf vein structures. On the other hand, leaf category recognition by making use of the external features along with vein and color was performed with Probabilistic Neural Network [16].

3.Proposed Methodology

3.1 Data set preparation

Images were collected from Dicotyledon plants (Rose Leaf, Cucumber Leaf). Three different sets from each plant were considered based on leaf age (i) young, (ii) mid-aged, and (iii) old. Again, each set has two subsets based on the leaf side (i) the front side and (ii) the reverse side. An example of the images from each species is included in the following Figures. Hardware augmentation was performed on each specimen and captured video using a high-frequency camera.

In the Dicotyledon group, there were 180 images, of which, 90 images were from Rose leaf and 90 images were from Cucumber leaf. Among the images from rose leaf, 15 images for front-young, 15 images for front-middle-aged, 15 images for front-old, 15 images for reverse-young, 15 images for reverse-middle-aged, and 15 images for reverse-old types. On the other hand, from among the images of cucumber leaf, front-young, front-middle-aged, front-old, reverse-young, reverse-middle-aged, and reverse-old types correspond to 15,15,15,15,15 and 15 images, respectively.

3.2 Image Preprocessing

The dimensions of the initial images were different. Also, some images had leaf-edge, which is against the primary intention. Point to be noted that for this experimentation, only vein pattern was taken as a feature and all other features, such as leaf-shape, color, etc were eliminated. Therefore, to achieve this goal, two-step preprocessing was performed on the corresponding dataset: (i) First, the green channel was extracted from the original images, which contains most of the valuable information. (ii) Then, the center port ion was pulled out from each image. In this step, multiple instances were created from each image with resolution 64x64, 32x32, 16x16, 8x8, and 4x4. The center point of an image was calculated from the height and width of each image. Only one segment was taken from an image.

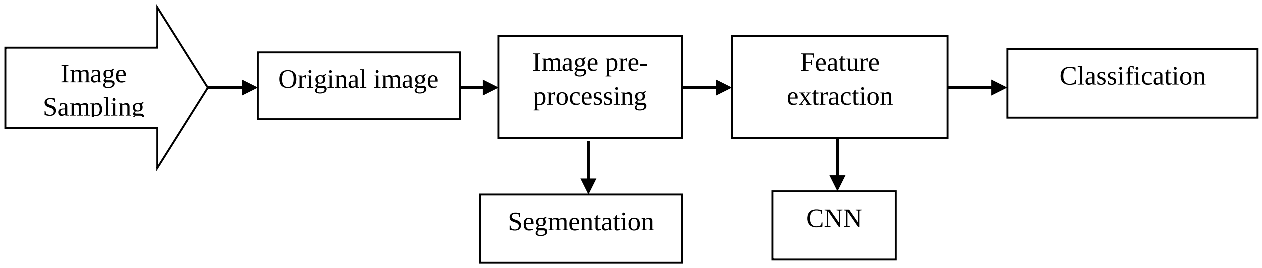

Figure 1. Steps for utilizing vein morphometric for plant disease classification

3.3 Post-processing

The pre-processed images were unbalanced with different numbers of images from each group. Additionally, Machine Learning models work with numerical data. For these reasons, two steps of post-processing were carried out: (i) The minimum number of images was collected for Cucumber mid-aged front-sided image group with 100 samples. So, the dataset was down-sampled by selecting 100 images from each group. (ii) Next, each image was converted into a NumPy array, flattened, and saved into a '*.csv' file. Each row in a file represents a single image, while the columns signify the flattened grayscale values for that image.

4.Residual Neural Network for Plant leaf disease Classification

4.1 Dataset Formulation and Feature Description

The dataset, prepared as described in Section 3.1 was fed directly into the model after subdividing it into training-validation-test sets. The only feature that was utilized in this research was the vein-texture from green-channel images, which was the aim of this work. All other probable features were eliminated for the experimental purpose and no other segmentation processes were involved in this proposed work. The imageset was split into 80% training, 10% validation, and 10% testing dataset. The test indices were selected randomly from each leafs.

4.2 Residual Block

The implementations of this paper are based on residual blocks. In residual network, the dimensional convolution layers were used with three different filters. For filter f1 and f3, a 1x1 kernel was integrated. On the other hand, a 3x3 kernel was used for the f2 filter. In all cases, the deployed stride was 1x1. There are three main stages of each residual block. All the stages are almost similar, except the first stage having a 2x2 max pooling layer after the very first Conv2D layer. Between two subsequent Conv2D layers, batch normalization followed by the ReLU (Rectified Linear Unit) activation layer was added. At the end of each stage, the stage-outcome is added with the original image and passed through a ReLU activation layer before starting the next stage.

4.3 Methodology

The block diagram for the applied model is given in the following figure. The model takes an input image and performs zero-padding of size 1x1. Then, each image passes through a 2D convolution layer, where a filter of size 64 with kernel size 5x5 and stride 1x1 are applied. After that, the model performs batch normalization, applies ReLU activation, and a 3x3 max-pooling with stride 1x1. Next, four residual blocks, each with three filter sizes are applied. The outcome of the residual blocks is passed through a 2x2 average pooling layer. Then, there are two dense layers, the first one with 4096 neurons and the second one with 2048 neurons. Now, in the case of a cotyledon identification scheme, the model applies an extra two dense layers (1024 and 512 neurons, respectively) before the final dense layer with 2 neurons. However, for leaf disease classification, after a dense layer with 2048 neurons, the model directly applies the final dense layer with 4 neurons. In all dense layers, ReLU is used as the activation function, except the final layers, where softmax is the activation function.

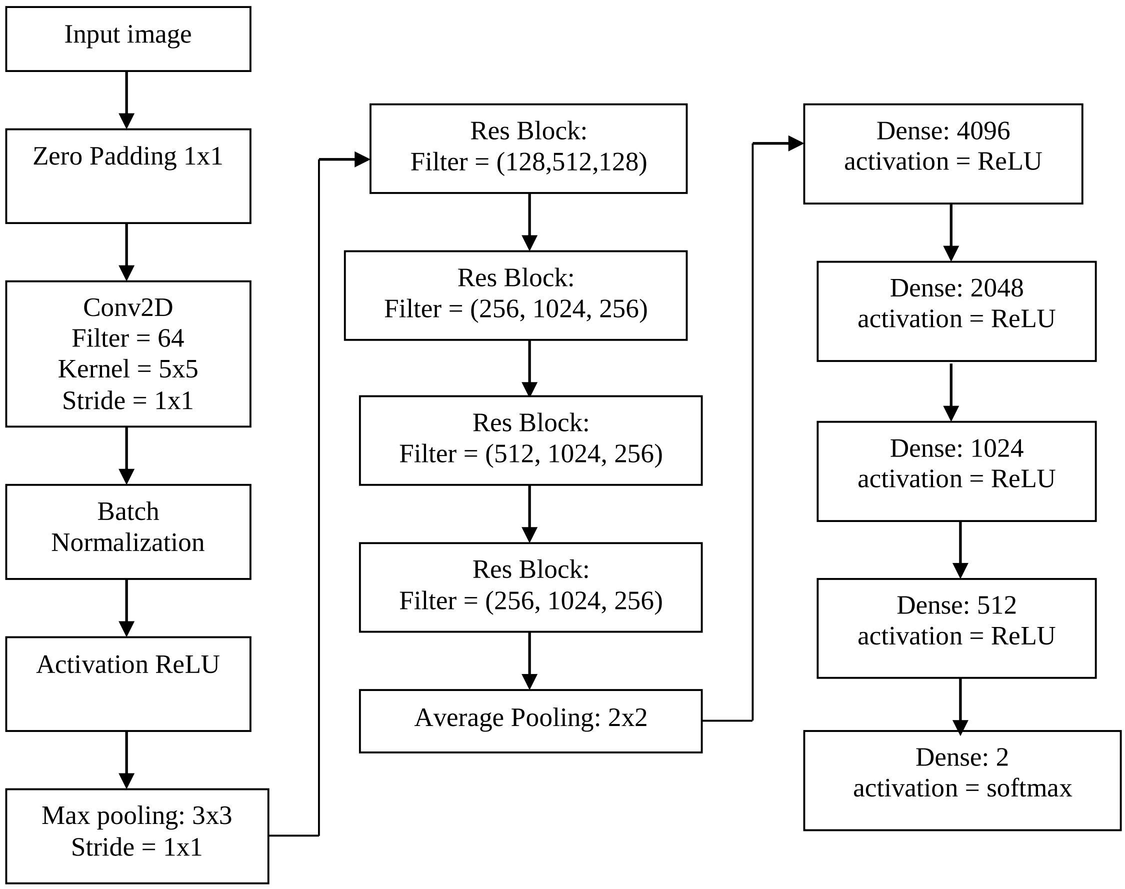

Figure 2. Implemented model structure

The novelty part of this network is that it is, in reality, a Residual -Dense hybrid construction. For leaf disease analysis, a Residual network following several Dense layers was found efficient in classifying images. As for ResNet152 V2, it is primarily based upon Convolution layers and there are no Dense layers embedded into it. In the case of disease identification, the batch size was 32. Similarly, for leaf classification, it was 8 (except for 8x8 pixel images in species classification, where the batch was 32).

5.Results and Discussions

The results for classifying plant leaf diseases classification are unified in the following table. Similar to plant leaf disease identification, the highest accuracy was achieved for images with resolution 64x64 pixels, and the lowest accuracy was for 4x4 pixel images. It can be observed that for 64x64 dimension images, the accuracy was as high as 85.38%. For 32x32 and 16x16 resolution image sets, the performance was 71.16% and 61.42%. However, for 8x8 and 4x4 resolution dataset instances, the performances were only 47.86% and 43%, respectively.

For plant leaf disease classification the confusion-matrix species classification for the highest accuracy implementation (64x64 image-set) is provided in Table 2. Therefore, the applied ResNet performed better than ResNet152 V2 model.

Table 1. Results for plant leaf disease identification using Residual network

No.	**Image Dimension**	**Test accuracy (%)**
1	64x64	91.18
2	32x32	81.08
3	16x16	63.14
4	8x8	65.35
5	4x4	59.48

Table 2. Results for plant leaf disease classification using Residual network.

No.	Image Dimension	Test accuracy (%)
1	64x64	85.38
2	32x32	71.16
3	16x16	61.42
4	8x8	47.86
5	4x4	34.00

As the results depict, high dimension image set helps to gain significantly high performance easily. However, low-resolution images can be classified by using deeper neural networks. Additionally, performances in the cases of leaf disease identification were noticeably higher than disease classification. It can be due to the number of images per class. Deeper network structures require a larger dataset. As for the change in dimension, Table 1 and 2 clearly shows that performance improves significantly with increasing resolutions. Nonetheless, the model was even able to achieve significant accuracy (34%) for 4x4 pixel classification, which is much better than 25% (blindly classifying all data into one class).

Table 3. Results for the implementation with the highest (64x64 pixel image-set)

Plant Leaf	Precision	Recall	F1 Score
Rose	0.95	0.87	0.91
Cucumber	0.86	0.72	0.78

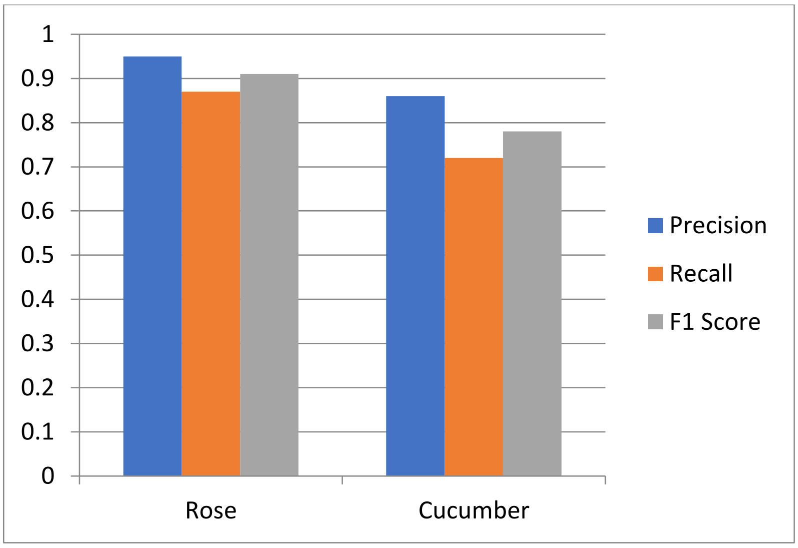

Figure 3. Results for the implementation with the highest (64x64 pixel image-set)

Table 4. Confusion matrix for cotyledon-type identification based on 64x64 pixel image-set (highest accuracy)

T = True **P = Predicted**	**Rose (T)**	**Cucumber (T)**
Rose (P)	1892	280
Cucumber (P)	103	2069

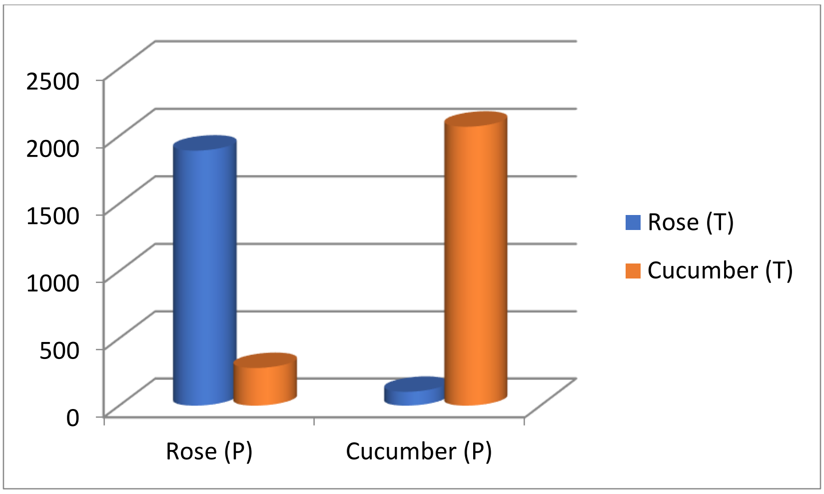

Figure 4. Confusion matrix for cotyledon-type identification based on 64x64 pixel image-set (highest accuracy)

6.Conclusion

This research paper introduces a novel processed center-focused green-channel image dataset for plant leaf disease identification and classification. Moreover, multiple instances of the dataset were created based on image dimension and shown the effects of image dimension on Residual Neural Network. It can be seen that if more data are added, low resolution is not a problem. On the other hand, a high-resolution image eradicates the necessity for more data. Any one of the two strategies is worth to be followed as per the situation.

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