Paper Review: 04

Title: An Effective Classification of Citrus Fruits Diseases using Adaptive Gamma Correction with Deep Learning Model.

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1. Introduction

Citrus fruits and plants are composed with Vitamin-C, and are used as source material in many agro industries. Recently, many researchers have tried to identify new machine based solution in order to predict the citrus disease primarily, from the field image processing. The above study has several limitations, such as local noise, orientation modification, color and texture of symptoms. Hence, effective feature extracting, and selection techniques are important for those application.

Citrus fruits are an important fruit in agricultural economy. Various methods for detecting and classifying citrus disease are presented, including preprocessing, shadow reduction, separating the object, K-means clustering, and blob detection.

2. Method

A method for automatic detection and classification of citrus diseases is proposed that consists of 2 stages including feature selection technique and classification through several classifier models like Naive Bayes, CART and NN with the help of multiple perceptron learning.

This paper presents a novel deep learning based citrus disease detection and classification model, which uses AlexNet architecture and adaptive gamma correction to improve the contrast of the applied citrus images.

The proposed AGC-A model involves four main processes namely pre-processing, segmentation, feature extraction, and classification.

3. Visualization

The stabilized gray level histogram is obtained by rounding the 8-bit grayscale image under highest pixel intensity. The pixel dynamic range of resultant images is covered which CE can be attained.

BF is applied to the test images that are in gray scale to remove the noise. It includes a distance-based domain filter part and a gray-value dependent range filter part.

Otsu's method is used in image processing applications for thresholding or converting a gray level image to binary image. It estimates a best threshold, portioning aforementioned 2 classes, to be negligible regarding their joint spread or intra-class variance.

4. CNN

Deep CNNs with ReLU nonlinearity are quicker than their corresponding units in various times, because their type of contrast normalization followed with local average pooling works mostly well.

We extend the net crosswise 2 GPUs, and utilize effectively sets half of the kernels (or neurons) on every GPU by one extra trick: the GPUs correspond only in definite layers. This lets us to accurately tune the quantity of transmission till it is a suitable fraction of the quantity of computation.

Local Response Normalization ReLUs have the attractive assets that they don't need input normalization to avoid them from oversupplying. Still, the pursuing local normalization system aids generalization.

We use a variety of lateral inhibition encouraged with the type create in actual neurons, to generate contest for large actions between neuron results calculated with various kernels. This normalization decreases the top-5 and top-1 fault rates with 1.2% and 1.4%, correspondingly.

Pooling layers in CNNs review the results of nearby sets of neurons in the similar kernel map. Overlapping pooling decreases the top-1 and top-5 fault rates with 0.4% and 0.3%, correspondingly.

AlexNet has 8 layers through weights, the 1st five are CONV and the left behind three are FC. The final FC layer feeds into a 1000way softmax that generates an allocation above the 1000 classes' label. The first CONV layer exacts the input picture through 96 kernels of size by a stride of 4 pixels, the second CONV layer takes as input (responsenormalized and pooled) output of the first CONV layer, the third, fourth, and fifth CONV layers are attached to one another.

Breiman presented a novel tree-based ensemble classification model in 2001. It comprises an integration of separate base classifiers where every tree is created utilizing a random vector sampled in an independent way from the classifier input vector.

5. AGC-A model

The presented AGC-A model is tested against Citrus Image Gallery dataset and the results indicate that the contrast level of the images are clearly enhanced by the AGC method which will helps to improvise the detection performance.

The Otsu based segmentation process yielded better segmented images, which improved the classification outcome of the presented AGC-A model.

The presented method clearly classifies a collection of images under blackspot, 77 images under cancker, 16 images under greening, 22 images under healthy and 15 images under scab type.

The presented AGC-A model accurately detects five different types of diseases with a minimum FPR and FDR of 0, maximum sensitivity of 94.74, specificity of 100, accuracy of 99.32, F-score of 97.29, G-measure of 97.33 and kappa value of 96.91.

The presented model clearly detects Greening disease, Scab disease and Healthy with minimum FPR and FDR of 0, maximum sensitivity, specificity, accuracy, F - score, G-measure and kappa value of 100 respectively.

6. Model Visualization

Table 7 shows that the LDA model offers poor black spot disease identification results, while the W-KNN model shows slightly better outcome. The EBT and DT models show moderate as well as identical detection results, while the M-SVM model offers optimal black spot disease identification with the least FPR and FDR value of 0.

Table 8 offers the results of various models on the detection of canker diseases in terms of FPR, FDRand accuracy. The AGC-A model offers optimal canker identification with the least FPR and FDR value of 2.77 and 2.53 respectively.

The M-SVM model offers competitive identification outcome with the minimum FPR and FDR values of 0.009 and 0.80 respectively. It also shows supreme canker disease identification with the highest accuracy value of 98.00.

Table 9 shows that the EBT, DT, W-KNN, LDA and M-SVM models show poor performance in terms of FPR, FDR and accuracy. The AGC-A model achieved the highest accuracy value of 99.32, while the M-SVM achieved the lowest FPR and FDR value of 0.02.

Table 10 offers results of various models on the detection of greening diseases. The W-KNN model exhibits the worst identification performance.

The W-KNN method offers ineffective outcome with the minimum accuracy of 93.80, the EBT and LDA models offer moderate as well as identical detection results with the same FPR and FDR values, the DT model shows slightly better outcome, and the M-SVM model offers competitive identification outcome.

Table 11 provided the outcome attained by different classifier models on the identification of all citrus diseases. The compared LDA model exhibits ineffective classification, while the W-KNN model offers slightly manageable results.

7. Conclution

This paper has presented an effective deep learning based citrus disease detection and classification model. The model accurately detects different types of citrus fruit diseases with the maximum detection rate of 97.29%.