A Machine Learning Approach to Classification of Okra

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Abstract:

Multiple machine learning techniques have been used for image classification purposes in agriculture. They can be applied to either roots, leaves or plants' detection and classification in order to assist farmers tasks. This paper aims to propose alternatives or solutions to post-harvest manual classification of okras by Japanese farmers in Okinawa. Thus, we implement Deep Learning to classify okras into categories pre-established by the Japan Agricultural Cooperatives. The classification features of okras in this study are their length and shape, and they classified into two: Class A and B. A set of pre-processing layers such as background noise cancellation, gray scaling and enhancement, image resizing and reconstruction are utilized to provide a higher detection rate. Moreover, a Convolutional Neural Network (CNN) is implemented to detect the patterns and predict the outputs.

1. Introduction

In recent years, the classification techniques through Artificial Intelligence have been playing a very important role in the agricultural field. Not only does it help detecting plant and soil diseases but also it does help optimizing the harvest and economic outputs as well [5] [7] [8]. Machine Learning integrated with Deep Learning has been largely used to detect, classify or predict plants' maladies[1] [2] [3] [6]and soil quality, develop "techniques" to optimize watering and fertilizer adequate amount, and predict the best weather conditions to cultivate plants according to their physiological properties.

This current study aims to develop a Machine Learning based techniques combined with few preprocessing layers to classify post-harvest okras. To better target customers and optimize the economical output, farmers need to classify, mostly manually, their products into different pre-established classes. The features used to classify products differ from plants, however they mainly turn around the color, the shape, the length and the size of products [2] [4] .

In this research, we focus on the classification of okras into 2 classes: Class A and Class B. They can be differentiated according to their shape and length. (class B < 13cm $\geq$ Class A). As in Figure 1 and 2, the shape of okras potentially plays an important role in the differentiation of the 2 categories. So does the length however as a more subtile mean. We gathered a total of 9750 images for the 2 classes and use, at first, multiple layers or preprocessing to reduce the excessive background noises, crop unnecessary parts of images (background), then resize the images. Then, we utilize a Convolutional Neural Network with multiple layers to predict the outputs of each image. This study demonstrates the potential of Machine Learning techniques for the automatic detection and classification of okras in Section 4, presents the relevance of automatic classification of post-harvest okras in section 5 by elaborating the preprocess steps in Section 3, then discussing the results before the conclusion in the last section.

(a)Class A

(b)Class B

Figure 1. Visual Difference

(a)Class A

(b)Class B

Figure 2. Visual Difference

2. Background

This study is part of a bigger vision of contributing to the technological advance of Agriculture in Africa, particularly in Senegal. Senegal's economy is strongly based on agriculture. Near 70% of the working working force is in some way related to the agricultural field. Agriculture in Senegal is mainly based in the production of groundnuts; peanut production being its engine since the 60s. The west African country used to be the World's first producer of peanut with 25% of the world's peanut production during that time. However, due to a lack of significant scientific advancement, irregular raining season, plant maladies and poor irrigation systems, Senegal never went beyond producing more than 1 million tons of peanut in a year and saw other countries like the United States, Nigeria or China increasing their production over the years. This study aims to bring, through an optimized preprocessing and CNN, a solution to the detection and classification issues of plants, furthermore to groundnuts maladies detection and prediction. Because of a lack of groundnuts data, we conduct the study using okra classification as means of showing the viability and potential of Deep Learning use to classify plants with similar features; especially considering the fact that some groundnuts maladies share similar patterns. The same techniques used in this study will serve as foundation for the next study which will focus on plants maladies' recognition and classification.

3. Preprocessing

The preprocessing being the first stage of this research consists of 3 steps that are detailed in the following subsections.

3.1 Image Cropping and Reshaping

As in Figure 1, 2 and 3, the okras consists of less than 30% of the input data. Moreover, in 80 % of images, the okra are horizontal while the rest remains vertical. Therefore, there is a need of matching images' position before removing the background noise then reshape all images on a common set of coordinates. In that way, the first step of this preprocessing consists of simply rotating vertical okra to horizontal. The second step consists of calculating each image's extreme points, meaning one point for each side of the okra (left, top, right and bottom). And from those point we calculated the center point of each okra. Finally, in order to unify the size of the okras for a faster process, we calculated the largest point interval of each axis (x, y) from all images and attributed it every images.

3.2 Image Resizing

The cropped and reshaped images in the Class A and Class B are respectively(476.5 x 465.5) and (498.5 x 468). The images have been resized to 1/10 on both axis. Class A = (47.65 x 46.55) Class B = (49.85 x 46.8). Image resizing has as purpose to decrease the process time by lowering the amount data (pixels) being fed to the convolutional neural network.
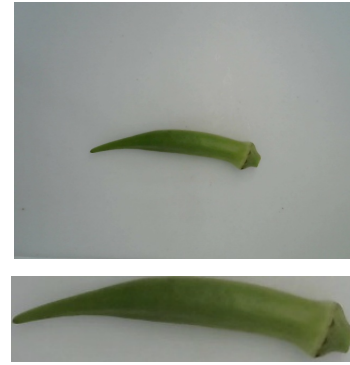

Figure 3. Image Cropping Process

3.3 Background Noise Removal

Most of images used in this study include noises. Noises include okra shades, borders and other background noises. In order to remove a maximum of those noises, we proceeded as follow:
1. grayscaling (Figure 5)
2. color inversion and binary enhancement (Figure 6)
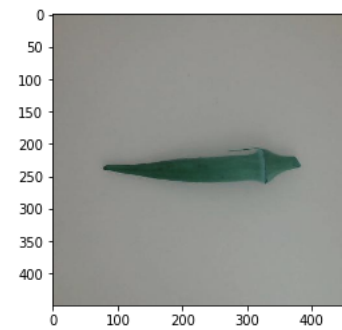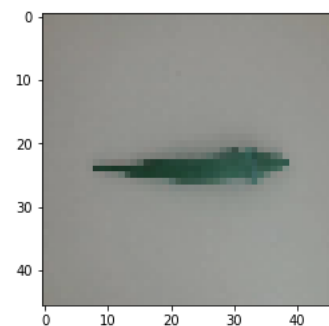3. substitution of shape by image(Figure 7)

Figure 4. Initial Image

Figure 5. Image Resized

4. Classification

The classification algorithm used in this research is the Convolutional Neural Networks (CNN). The CNN implements Deep Learning to Machine Learning processing [6] in

Figure 6. Grayscaling & Binary Enhancement

Figure 7. Substitution

the ultimate goal of classifying images without any user interaction. It has a set of multiple layers connected between them and can be composed of different types of layers such as convolutional layers, fully connected layers, pooling layers etc.

4.1 Convolutional Neural Network(CNN)

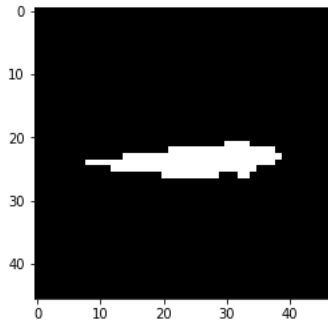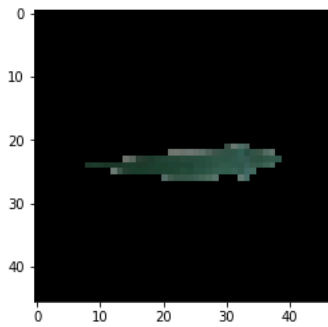The classification algorithm used in this research is the Convolutional Neural Networks (CNN). The CNN implements Deep Learning to Machine Learning processing [6] in the ultimate goal of classifying images without any user interaction. It has a set of multiple layers connected between them and can be composed of different types of layers such as convolutional layers, fully connected layers, pooling layers etc.

The proposed CNN in this study is structured as follow: Input, Hidden Layer1, Hidden Layer2, Output. The input is the first layer of the CNN architecture and the raw data was fed to the network through this layer. The input image size is 46 x 47 x 3. It is followed by 2 convolutional layers. The convolutional layers are used to detect and extract features within the images. Both the first and second convolutional layer share the same filter architecture, 32 different 3 x 3 filter. The rectified linear unit layer (ReLU) comes after each convolution layers and is known as the most commonly used rectifier unit for neuron outputs. [4] After the ReLu, is placed a pooling(max-pool is 2 x 2 in this study) which contributes in the reduction of the input size(width x height) for the following convolutional layer. We utilize a "Sigmoid" function as an activation function of the neural network within the last layer in order to determine the final output.

5. Experimental Evaluation

Training samples improve model performance in disease detection [1]. For this reason 80% of okras are used for training. In this study, we run 4 different tests (table 2). Test 2((R), (G), 64 x 48), test 3(R, G, Remove Noise(RN)) and test 4(R, G, RN, Image Cropping)) modify and/or add a new preprocessing layer to their respective previous test; each preprocessing layer aiming to reduce background noise, reshape or resize the input data. All trainings were executed with 3 iterations (epochs = 3). Each test is shown to have a lower processing time compared to the previous one.

Moreover the accuracy, as shown on table 2 , gets higher when a new preprocessing layer is added. This shows that each new preprocessing layer contributes in decreasing the processing time while increasing the accuracy of the classification. It can also be said that the classification gets more accurate with background noise cancellation, reshape and resize preprocessing seeing as the neural network architecture didn't change over the course of this study.

Furthermore, seeing as the combined preprocessing layer in the final test (Test 4) provides the highest accuracy and lowest preprocessing time, we improve its CNN architecture by modifying the number of filters from 32 to 256 and train 3 times (epochs=3) as initially and then 10 times(epochs =10). The final result shows that with a combined set of all preprocessing layers, a high number of filters and augmented epochs, the designed CNN architecture can effectively detect and classify okras with an accuracy of 84.67%.

	Predicted A	Predicted B
Actually A	**True Positives** **4227**	**False Positives** **687**
Actually B	**False Negatives** **847**	**True Negatives** **2042**
Precision = 86.01%		Recall = 83.3%

Figure 8. Precision & Recall

In a different test designed to calculate the precision and recall (Figure 8), it is shown that the precision is higher than the recall. In other words, it shows that the class A is less mistaken for class B, as class B would be mistaken for class A. It can be explained by the fact that the class B contains

Table 1. Definition of Preprocess terms

Term	Definition
R	Resize into smaller scale
G	Grayscaling
RN	Remove backround noise
IC	Crop images on chosen coordinates

Table 2. Loss, Accuracy and time

process	input size	accuracy [%]	time [sec]
R, G	50 x 50	79.66	50
R, G	64 x 48	81.61	35
R, G, RN	64 x 48	81.76	42
R, G, RN, IC	46 x 47	83.79	33

share some common features with the class A. The shape as in Figure 2 can be similar while the size remains slightly different. The similitude could potentially be the main reason of the low recall percentage in this study. The images used in this research were priorly classified manually by farmers. It has been noticed that the actual manual classification of okras do not only take the established standards. They also take into account the "color" and "pigmentation" as classification features. Thus, this classification based on each farmer's working experience and point-of-view is the main reason the CNN algorithms have been induced in this study. The classification accuracy as well as the precision and recall could potentially grow higher if only "shape" and "color" were the only features considered in the classification.

Optimizing the preprocessing steps has been shown to not only decrease the process time but also to gradually increase the accuracy. Over the preprocessing steps, adding filters allows to better discern, detect the okra and reduce the noises around it. Furthermore, resizing the inputs to 1/10 of their initial size compared to a standard non-relational reduction has been demonstrated to accelerate the process time by -30%.

6. Conclusion

In the previous years, myriad of researches have been done to bring tangible solutions based on Artificial Intelligence with Machine Learning. Agriculture is one of the domains rapidly growing with the implementation and assistance of those technologies. In present study, CNN has been combined with a set of preprocessing techniques to bring solutions to okra classification issues. Using a set image cropping, reshaping, resizing and background noise cancellation as preprocessing, we designed a convolutional neural network that can classify okra into 2 given categories with an accuracy of 84.67%. Each layer of preprocessing has been shown to contribute to a better processing time while increasing at low margins the classification accuracy. Further studies will be done using a higher number of images and more consideration of "color" and "pigmentation" as features in order to achieve a higher classification accuracy. As mentioned upper, the preprocessing and CNN used in this study will lay the foundation for further studies in plant maladies classification. The algo-

rithms used in this study will be also subject for improvement in future studies.

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