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A Method for Detecting and Segmenting Infected Part of Cacao Pods

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Abstract: Farmers and agricultural technicians regularly monitor the well-being of their crops. But at present they rely on visual inspection to assess the degree of infestation of their crops, resulting to several errors and inconsistencies due to the subjective nature of the assessment procedure. To improve the inspection procedure, this research shows a method for detecting and segmenting the infected parts of the cacao pods based on K-means algorithm supplemented by a Support Vector Machine (SVM) using image colors in L*a*b* color space as features. The highest attained accuracy was 89.2% using four clusters. Results of this research provides promise in the implementation of the proposed framework in developing a more accurate assessment of infestation level; thus, potentially improving decision support for managing cacao diseases.

Key Words: *Cacao, Image Segmentation, Color Features, L*a*b* Color Space, Machine Learning*

1. INTRODUCTION

Philippines used to produce about 20% of the world's cacao (Tupas, 2014). However, pests and diseases plagued the farms during the 1980s, leading to the fall of the Philippine cacao market. Nowadays, the Philippines accounts for only less than 0.5%.

Several diseases affect cacao pods worldwide, losing up to 40% of production annually (Ploetz, 2007). Some farms even suffer up to 90% of losses in plantations (Hebbar, 2007). The Philippine Bureau of Agricultural Research reports the following most common cacao pests and diseases in the Philippines: *black pod rot, vascular streak dieback, cacao pod borer, helopeltis,* and *cacao stem borer*. Black Pod Rotting alone causes 20 to 30% pod losses, and kills up to 10% of trees annually through stem cankers (Guest, 2007, Adomako, 2007).

To reduce the damage of pests and diseases in the cacao industry, visual surveillance of cacao pods are done. As of today, farmers and agricultural technicians manually perform the visual inspection of the pods while comparing them to a visual aid to assess the severity of the disease. These aids come in the form of a severity index for cacao pod rot based on a scale of 0 to 5 (see Figure 1 below), patterned from Alvindia and Acda's work on managing anthracnose of mangoes (Alvindia & Acda, 2015).

However, the problem with the current indexing scale is that it is subjective and very labor intensive. The assignment of the index can be inconsistent depending on who is tasked to do the evaluation. Thus to potentially improve the efficiency and eliminate subjectivity bias in the assessment of the infestation level, a proposed solution is to develop a technology to perform the task with minimal human interaction. This paper explores the use of image processing and machine learning techniques to serve as the foundation for an automatic and efficient measurement of infestation level on cacao pods, enabling precise dosage for treatments, quantitative measure for disease spreading rate, and improved decision support for cacao disease management.

Fig. 1. Sample visual aid used to assess the severity of the disease.

Color is an integral feature in object classification. Images taken from cameras are usually in the red-green-blue (RGB) color space. Classification based on RGB have been implemented in detecting raisins (Omid, 2010), skin defects in citrus fruits such as oranges (Blasco , 2009; Lopez-Garcia, 2010; Wang 2013), strawberries (Xu, 2010). The RGB color space however is dependent on lighting conditions. Hence, other color spaces are also used in image processing to extract features and segment objects. Unlike RGB, HSI decouples the brightness of the image from its color components. HSI stands for Hue, Saturation and Intensity (Jhuria, 2013; Akin, 2012; Aibinu, 2011). Hue stands for the pure color, saturation for the color contrast, and Intensity for the brightness of the image. The system should produce the same results regardless of the time of day and weather conditions, the HSI is used to achieve this. The Ohta Color space (Guo, 2004) is represented as three orthogonal features. The conversion from RGB to Ohta color space is linear and computationally inexpensive as compared to HSV and other color spaces. This is particularly important in using mobile devices where memory, processor and battery usage must be taken into consideration. La*b* is also another feature space used in image classification and segmentation. The color information is stored mainly on a* and b* channels. Using this feature space have been found to reduce image segmentation processing time of apple skin defects. (Dubey, 2012) The a* channel in La*b* was used in detecting the dominant color of strawberries (Xu, 2010)

K-Means clustering is a clustering technique commonly used in image segmentation. It was used to grade strawberries (Xu, 2010) and apples (Dubey, 2012) based on color, shape and size. Another image clustering techniques used for fruits is Fuzzy Image thresholding. Kamalakannan (2012) used it for detecting surface defects in mandarin fruits.

Classification of fruits and disease used different learning techniques such as Artificial Neural Network (ANN) (Xiao, 2010; Nanaa, 2014; Jhuria, 2013), Support Vector Machine (SVM) (Wang, 2013), Linear Discriminant Analysis (LDA) (Xiao, 2010) Classification Trees (Kamalakannan, 2012), Bayesian Discriminant Analysis (Blasco, 2009). With sufficient data, ANN gives favorable results on most classification task. This however requires a lot of training data and can be computationally expensive. SVM requires less data than ANN and is less computationally expensive.

2. METHODOLOGY

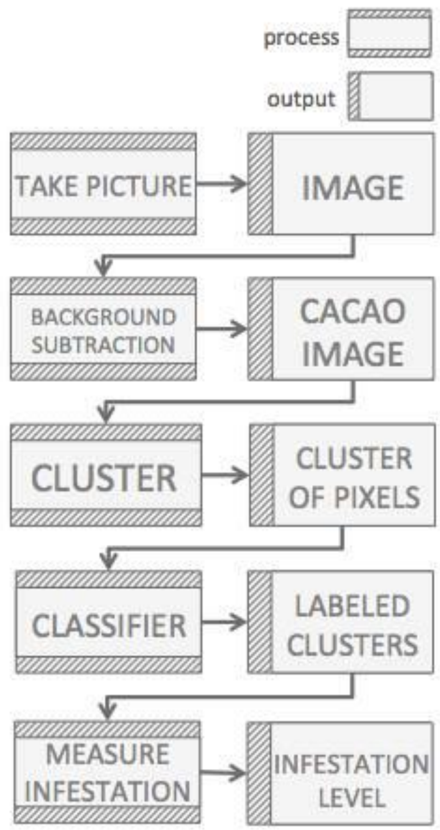

Fig. 2. Data flow diagram of the proposed framework for measuring infestation level.

Measuring the infestation level of the pods required four major steps shown in figure 2: (Step 1)

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collecting images and pre-processing; (Step 2) clustering for image segmentation based on colors; (Step 3) classifying the clusters as either healthy or infected; and (Step 4) computing for the infestation level.

The first step is to take a picture of the cacao pods and remove their backgrounds. Some guidelines for the pictures were implemented to ensure the quality and minimize the variability in the kinds of images that will be processed.

The second step involved the segmentation of the infected and non-infected parts of the pods. The pixels having similar colors are grouped into clusters with the idea that pixels of the infected parts of the pod (can be referred to as infected pixels) are similar in color and would be grouped together in a separate group from pixels of the healthy parts of the pod (can be referred to as healthy pixels).

The next step classifies these clusters to be either healthy or infected. The grouping from the previous step is done automatically with a clustering algorithm having a similarity measure as the only criteria for grouping. The clustering algorithm provides no information on whether the clusters are groups of healthy pixels or groups of infected pixels. Which is why a classifier needs to be trained to recognize which clusters are infected clusters and which clusters are healthy clusters and label them accordingly.

The last step combines all the clusters labeled infected and all the clusters labeled healthy to compute their proportion to the cacao pod. The number of pixels was used as the unit for estimating the proportions.

2.1 Data Collection and Pre-processing

The images were collected from various sources, some lifted from the internet and some photographed from the fields of Central Luzon State University. Our criteria for gathering images are: (1) the image contains only a single cacao pod; (2) the infected cacao pod has visible manifestations of the disease, e.g. spotting, rotting, or discoloring; (3) the image size is at least 360x480 pixels; and (4) the cacao pod occupies approximately 75% or more of the image. Figure 3 shows some images of the diseased cacao pods. We collected 35 images, 30 for training, and 5 for testing. The background of the images were manually removed to eliminate its effect on the training and evaluation of the framework.

2.2 Detection and Segmentation of the Infected Part of the Cacao Pod

We adopted Dubey's (Dubey et al., 2013) solution of using *K*-Means algorithm for a simple and straightforward image segmentation. Following their work, we converted the image from the RGB color space to the L*a*b* color space. *Commission Internationale d'Eclairage* (CIE) designed the L*a*b* color space to match how humans perceive differences in color and luminance (Szeliski, 2010), thus making it a good color space for computing distances. It is composed of a luminosity or lightness dimension (L*) and two chromaticity or color dimension (a*b*). Isolating the color information to two dimensions (in L*a*b*) makes it computationally more efficient than having the color information spread to three dimensions (in RGB) (Dubey et al., 2013).

Fig. 3. Sample images from the data set of diseased cacao pods.

The pixels are then clustered in the a*b* color space using the *K*-Means algorithm. *K*-Means is a clustering algorithm that tries to group similar objects (in this case pixels) together. The variable k is a user defined parameter that sets the number of clusters to be formed. More specifically, varying k would force the data to be grouped into k clusters. The general idea of using a clustering algorithm for image segmentation is that the infected part of the fruit would be similar in color (represented by a*b*) and will tend to group together in a separate cluster from the healthy part of the fruit.

The *K*-Means algorithm starts by randomly selecting k pixels as the initial centroids for the clusters. The centroids represent the clusters and is used to determine which pixels belong to it. The rest of the algorithm is an iterative process and proceeds as follows:

> (Step 1) Assign all the pixels to the cluster with the centroid closest to them. We used the Euclidean distance in computing for the

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similarity – the less the distance being the more similar they are.

(Step 2) Compute for the new centroids of each cluster by getting the mean of all the pixels within that cluster.

(Step 3) Repeat Steps 1 and 2 until the clusters do not change anymore.

After clustering, the image is then segmented based on the clusters formed, i.e. each cluster of pixels form a separate image.

Afterwards, manual labeling of formed clusters were done due to the limitations of the clustering algorithm to automatically identify which pixels are infected and which are not. Hence, automating the labeling process was now viewed as a classification problem. For the next step, we used a Support Vector Machine (SVM) to classify infected pixels from healthy pixels.

SVM is a supervised machine learning algorithm used for classification and regression tasks. Training a classifier requires a set of features that represent the data points and discriminate between their classes. In this case, the data points are the clusters of pixels obtained from the K-Means algorithm. We observed that humans rely on color to distinguish the infected part of the fruit. Therefore, it is logical to choose color as the main feature for the classifier.

After labeling the clusters, the average values of a* and b* of the pixels within the cluster, were used as features for the classifier.

3. RESULTS AND DISCUSSION

3.1 Image Segmentation based on K-Means Algorithm

We segmented the images using the *K*-Means algorithm with different values of k. Ideally, we want k to be such that the formed clusters (hence, the image segmentation results) contain either infected pixels only or healthy pixels only. For this experiment, we tried setting k to 2, 3, and 4. Figure 4 shows the results of the segmentation. When k is set to 2, it is expected that one cluster will contain the infected pixels and the other will contain the healthy pixels. But in our data set, most of the images cannot be separated well using only two clusters. Figure 4 (Right) is an example of this. Its healthy pixels had a yellow green color while its infected pixels had parts which are dark brown and parts which are light brown, causing one cluster to mix healthy and infected pixels. Setting k to 3 gives satisfactory results, wherein a few pixels still get mixed up especially those in the boundary of healthy and infected. Figure 5 shows this slight mix up where a few green healthy pixels were grouped together with infected pixels at $k = 3$. It also shows that increasing k to 4 separates the green healthy pixels further from the infected cluster, giving a more precise segmentation than 3.

3.2 Classification of Segmented Clusters

We trained a SVM classifier with a quadratic kernel on the different values of k. Figure 6 shows a scatter plot of the cluster centroids in a*b* space. The colors tell whether the cluster is infected or healthy. The 'x' symbols represent the points that were misclassified. We chose a quadratic kernel because the scatter plot shows that the clusters cannot be easily separated by a linear function.

Table 1 shows the performance of the SVM classifier using the mean values of the channels in a*b* color space as features. The values were computed from a 10-fold cross validation, i.e. the SVM classifier was trained and evaluated 10 times with each iteration having 90% randomly selected data points for training and 10% randomly selected data points for testing. At $k = 2$, the SVM classifier had a low accuracy. Poor segmentation of the images during the clustering step affected the classifier leading to a low accuracy. Increasing k to 3 and 4 significantly improved the results, having up to 86.7 and 89.2% accuracy respectively.

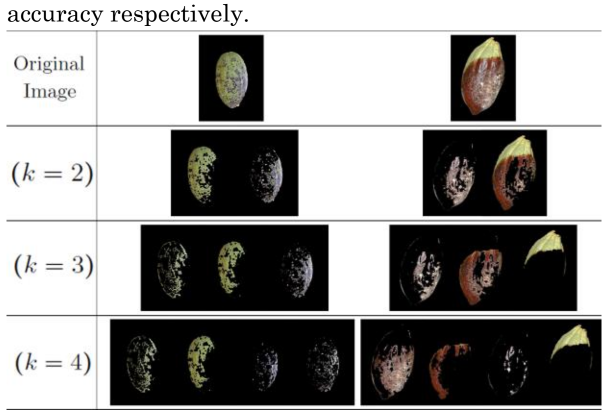

Fig. 4. Results of *K*-Means Images Segmentation for 2 sample images at different values of k.

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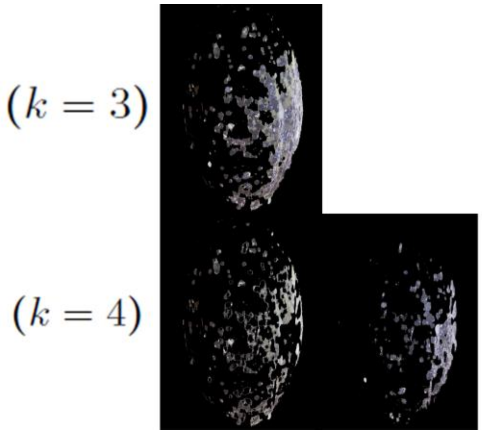

Fig. 5. An example of an infected cluster at k = 3, slightly mixed with a few healthy pixels, being further separated at k = 4.

We tried to see how much the classifier would improve by having more clusters, but after doubling the value of k the accuracy did not increase. It is interesting to observe that at k = 8, the accuracy actually went down. This is because the number of samples and the granularity of the samples increase as the number of clusters increase. Consequently, more number of points are near the boundary – where the model is most likely to misclassify. General trends with different levels of k were also observed for both sensitivity and specificity.

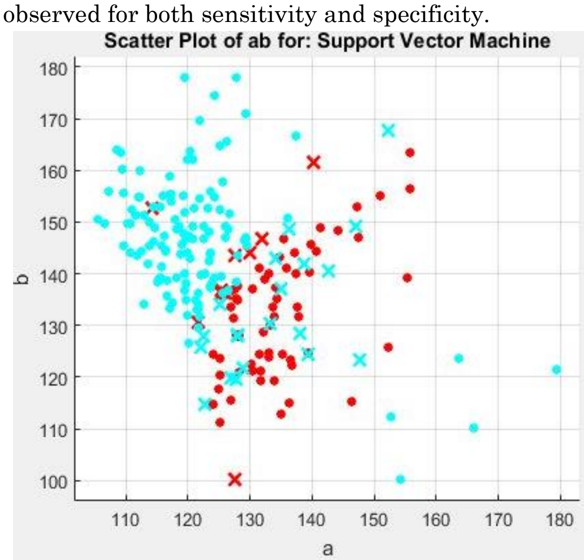

Fig. 6. Scatter plot of the centroids of each cluster in a*b* space.

Table 1. Performance of the Support Vector Machine classifier using a*b* features.

k	Accuracy (a*b*)	Sensitivity (a*b*)	Specificity (a*b*)
2	60.0%	77.1%	36.0%
3	86.7%	88.6%	84.8%
4	89.2%	90.6%	88.1%
8	87.1%	89.7%	85.3%

4. CONCLUSIONS

In summary, we used the K-Means algorithm to group the pixels into healthy and infected clusters. The clusters were then labeled and used to train an SVM classifier that would automatically determine which clusters contain infected pixels and which clusters contain healthy pixels.

Based on the criteria described above, a bigger k would generally give better results, on both K-Means image segmentation and SVM classification. This is because increasing the number of clusters lessens the variance within clusters; thus, decreasing the chances of mixing healthy and infected pixels in the same cluster. However, more clusters would mean additional computational complexity and longer processing times. Our experiments show that using 4 clusters provides an optimal balance between segmentation performance and computational complexity.

The SVM classifier gets confused with the healthy reddish colors of the cacao pods because the color is similar to some cacao diseases. The varieties of the cacao may be identified first and train different models catered to the green variety and red variety of the cacao pods to avoid this confusion.

An extension of this research can include a background subtraction algorithm to automate the process of removing the backgrounds. Other clustering algorithms and classification algorithms may also be explored to improve performance in terms of accuracy and processing time.

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