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An Objective Classification Approach of Cacao Pods using Local Binary Pattern Features and Artificial Neural Network Architecture (ANN)

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Abstract

Objectives: Cacao is considered the "food of the gods" and is one of the leading crops of the tropical world. The differentiated use for both food and non-food of cacao is the reason why it has been gaining recognition around the world. Despite this, cacao production is said to be declining for a variety of reasons. One of these is the possible contamination among the harvested pods due to the manual way of performing classification and segregation of cacao pods during the harvest period. Traditional approach or the manual way of classifying whether the pod is healthy or not is very subjective, which may give erroneous results, and mixing of healthy and unhealthy pods may lead to contamination once they are transported and stored. Hence, we develop a study to make an objective approach that performs cacao pods classification by discriminating healthy cacao pods from unhealthy ones using Artificial Neural Network (ANN). **Methods:** This study presents a Cacao Pod Classification System that will automatically classify cacao pods (i.e. healthy or not healthy) during the harvest period. We leverage imaging technology and machine learning techniques to create a classifier that performs binomial classification. Color Histogram (CH) and Local Binary Pattern (LBP) features were used as input to the Artificial Neural Network (ANN) classifier. **Findings:** Experiments reveal that the approach successfully extracts features from the captured images of cacao pods and provides efficient results in terms of the four performance measures (i.e. accuracy, precision, recall, and f1-score) giving an accuracy rate of 98.3% in particular, which is superior among other classifiers tested such as the Support Vector Machine (SVM) and Logistic Regression (LR). **Novelty:** Artificial Neural Network classifier was found to be superior from other classifiers tested in classifying healthy and unhealthy cacao pods along with color histogram and local binary pattern as features used in the study. **Application:** The pilot test of the application was performed in a 5-hectare privately owned cacao farm situated at Poblacion, Initao, Misamis Oriental, Philippines.

Keywords: Image Processing; artificial neural network; cacao pod; classification; feature extraction; segmentation

1 Introduction

Theobroma cacao, also known as "cacao" is one of the leading plantation crops of the tropical world. This crop is said to be the major ingredient in making chocolates and no other crop can substitute it as far as the chocolate industry is concerned. Additionally, cacao is said to be used not only for food consumption but is also gaining recognition in the fields of medicine and cosmetics. This tropical crop grows best in a humid climate with adequate rainfall. The Philippines is one of the countries in Asia that has an advantage in the production of cacao because of its location and efficient climatic condition. Philippines' cacao production level reached 35,000 MT by 1990. However, for many reasons, cacao production was reported to be declining. According to the Philippine Cacao Industry Roadmap majority of the cacao farms in the country are being owned and managed by small holding farmers. These farmers are mostly undergraduates who learned about farming through their ancestors or through personal experience. Additionally, majority of them have limited technical skills and knowledge on managing their farms. Further, farmers have limited access to relevant and updated data, information, and knowledge which they can use to further increase their yield. Additionally, farmers are performing the manual way of inspecting, assessing, monitoring, and classifying whether the cacao pod is healthy or not during the harvest period[1,2]. This is the problem that we have identified, farmers are doing the manual way of classifying whether the cacao pod is healthy or not during the harvest period. From pollination, cacao pods form, mature, and ripen between 160 and 180 days. Ripeness is indicated by a change in color when green pods turn to bright green or yellow, or dark-red or purple pods turn to yellow or orange. Harvesting should be done every week during peak season and every two weeks for the non-peak season. Harvested pods may be stored for 7 days in a shaded area. Separate diseased pods from healthy pods right in the field to avoid contamination during transport and storage[3].

It's very important to separate diseased pods from healthy pods right in the field. Healthy cacao pods range in color from bright green to yellowish to orange or purple. On the other hand, unhealthy cacao pods contain small brown to black spots and the texture of the skin is rough compared to the healthy pods and some contain lesions that serve as points of entry of injurious fungi. The visual appearance of healthy and unhealthy pods may differ from each other, but there are times that the features are very confusing by merely visual inspection. Because of this, classification of pods is very subjective and the traditional approach (i.e., manual classification of diseased pods from healthy ones) gives erroneous results, and mixing of healthy and unhealthy pods may lead to contamination once they are transported or stored for 3 to 7 days[4]. Thus, to potentially improve the effectiveness and efficiency of managing the crops, a solution is to develop a technology to perform the task with minimal human interaction. Hence, there is a need to develop an objective method in classifying the cacao pods during the harvest period[5–7].

We leverage imaging technology[8–12] and machine learning techniques[13–15] to create a classifier that performs binomial classification with Color Histogram (CH) and Local Binary Pattern (LBP)as features input for classification. The Color Histogram feature was considered in the implementation of the study because of its numerous advantages such as simplicity in terms of manipulation, efficiency, and speed in computation and manipulation. This also represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color space or the set of all possible colors[16–18]. Moreover, the Local Binary Pattern (LBP) feature was also considered because it is a simple and efficient texture-based operator that labels pixels of an image by thresholding each pixel's neighborhood and treating the result as a binary number[19–21].

There have been existing studies that use different learning techniques for classification problems such as Support Vector Machine[22–24]; Logistic Regression[25] and Artificial Neural Network[26–31], although these classifiers performed well, however, we found out that the experiment reveals among the classifiers tested (e.g., Support Vector Machine, Logistic Regression, and Artificial Neural Network), the ANN gives favorable results on most classification tasks and showed a high value in terms of accuracy.

2 Materials and Methods

Figure 1 shows the conceptual framework of the study. It shows the relationship between the different modules of the system and how data travel across the system.

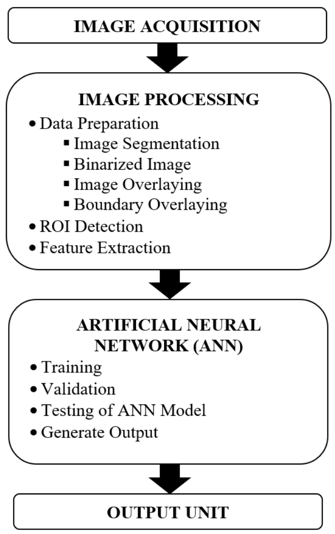

Fig 1. Conceptual Framework of the Study.

2.1 Experimental Set up and Procedure

Cacao Pods were placed inside a rectangular box (40cmX32.50cmX27cm) with a reasonable amount of lighting installed and then captured using a Logitech Web Camera with a max resolution of 720p/30fps in a constant distance of 20.5 cm automatically saved in a computer for data manipulation and analysis. Figure 2 presents the setup in capturing cacao pod images during our experiments.

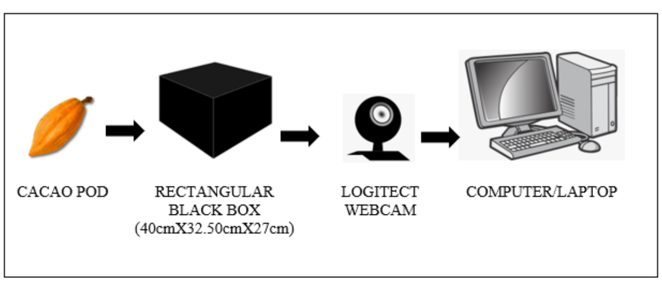

Fig 2. Experimental Set-up in capturing Cacao pod images.

Cacao pod images were saved in computer storage and pre-labeled accordingly. A total of 217 cacao pods were classified as healthy and a total of 201 cacao pods were classified as unhealthy, which were used as the ground truth.

2.2 Image Acquisition

A total of 418 images of cacao pod were captured and gathered for analysis (217 classified as healthy cacao and 201 classified as unhealthy cacao).Figures 3 and 4 present sample images of healthy and unhealthy cacao pods respectively.

Fig 3. Sample images from the data set of Healthy Cacao Pods.

Fig 4. Sample images from the data set of Unhealthy Cacao Pods.

2.3 Image Processing

Raw cacao image data will undergo image processing to extract features. These features served as input to the Artificial Neural Network (ANN) Architecture as shown in Figure 5

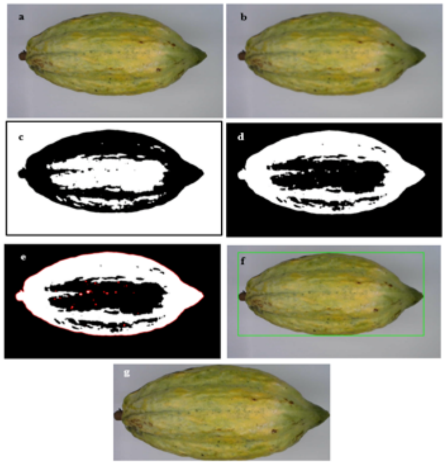

Fig 5. Data manipulation methods based on Image Processing **(a)** Load the original Cacao Pod Image; **(b)** Apply Gaussian Filter; **(c)** Apply Otsu's Method for Image Binarization; **(d)** Generate Complemented Image; **(e)** Trace Boundaries; **(f)** Locate the Region of Interest (ROI); and **(g)** Crop the Cacao Pod Image.

2.4 Feature Extraction

There were two features considered in the study that gave a high contribution to the classification performance. These features were the Color Histogram (CH) and Local Binary Pattern (LBP) features which served as input to the Artificial Neural Network (ANN) Architecture.

2.4.1 Color Histogram Features

Color Histogram feature was considered in the implementation of the study because of its numerous advantages such as simplicity in terms of manipulation, efficiency, and fast in computation. This represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color space or the set of all possible colors as shown in Figure 6. There were 418 samples and 768 features taken in each sample for Color Histogram (CH) features.

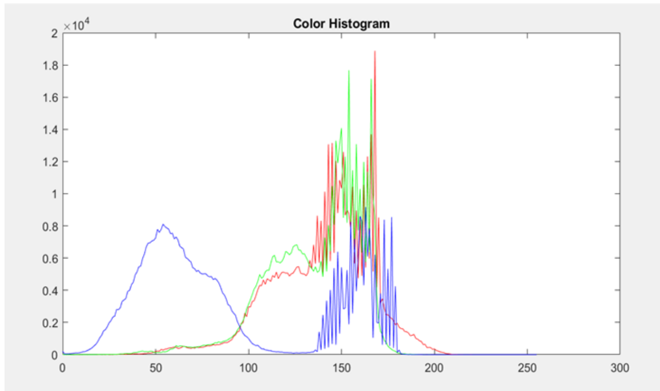

Fig 6. Loaded Cacao image with its Color Histogram features in graphical form.

2.4.2 Local Binary Pattern (LBP) Features

The Local Binary Pattern (LBP) feature was also considered because it is very efficient and a simple texture-based operator that labels pixels of an image by thresholding each pixel's neighborhood and gives a binary number as a result. We performed the following steps in Local Binary Pattern (LBP) for image feature extraction:

Step 1. Cacao image was converted into grayscale image.

Step 2. SP neighborhoods that surround the central pixel were selected for the calculation of each pixel (i_p) in the image. The coordinates of i_p are given by:

$$(i_{cx} - SRsin(2\pi p/P),\ i_{cy} + SRcos\ (2\pi p/P)) \tag{1}$$

Step 3. Center pixel (i_c) was taken and used as the threshold value for its P neighbors.

Step 4. If the value of the adjacent pixel is greater than or equal to the value of the center pixel then S is 1, otherwise 0 as shown in equation 2.

$$S(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{2}$$

Step 5. For LBP value: A binary number consisting of digits adjacent to the center pixel was written sequentially in a counterclockwise manner. The binary number is the LBP-central pixel code as shown in equation 3 and used as a characteristic selected local texture.

$$LBP\left(i_{p_x},\ i_{p_{xy}}\right) \sum_{P=0}^{P=1} S\left(i_p - i_c\right) *\ 2^P \tag{3}$$

Where:

i_c- the intensity value of the central pixel

i_p- the intensity of the neighboring pixel with index P

SP- is the number of sampling points on a circle of radius R (circular neighborhood). It controls the quantization of the method.

SR- determines the spatial resolution of the method or operator

There were 418 samples and 59 features taken in each sample for Local Binary Pattern (LBP) features.

2.5 Artificial Neural Network (ANN

The 827 total features (768 features for Color Histogram and 59 features for Local Binary Pattern) taken in each sample were fed as inputs for training and testing the Artificial Neural Network (ANN) classifier for classifying if the cacao pod is healthy or unhealthy as shown in Figure 7.

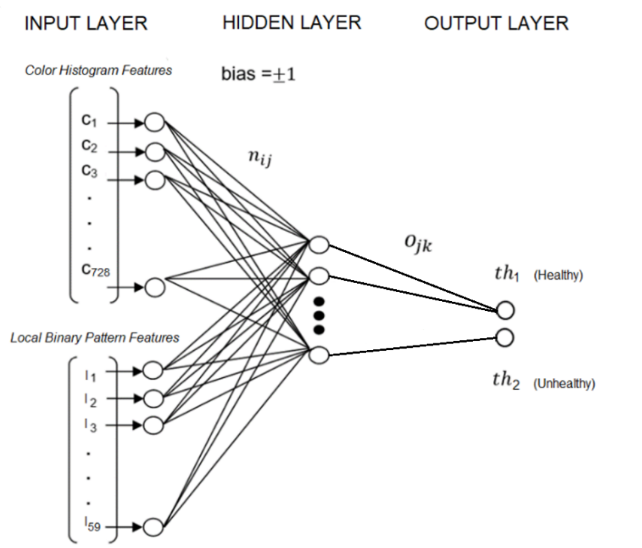

Fig 7. Artificial Neural Network (ANN) Architecture.

Color Histogram (CH) features and Local Binary Pattern (LBP) features represented by $(c_1, c_2, c_3, \ldots, c_{728}]$ and $(l_1, l_2, l_3, \ldots, l_{59}]$ respectively were the input vector for the classifier. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the input variables, a constant input bias of 1.0 was fed to each of the hidden layers; the bias was multiplied by a weight $th_1 th_2$ that characterize for unhealthy.

2.6 Output Unit

In this last stage, features were used as input to the ANN and the system will then automatically classify whether the cacao pod is healthy or unhealthy. Since Support Vector Machine (SVM) and Logistic Regression (LR) and Artificial Neural Network (ANN) have been tested to be efficient in building a classifier as shown in several studies[22–31], we considered these three (3) models as the most appropriate classification techniques to be used in building a predictive model. We conducted experiments utilizing each of these models and compared the results in terms of their performance measures (i.e., accuracy, precision, recall and F1-score) as shown in Table 1.

Table 1. Comparison of the performance of different classifiers for cacao pod classification

Classifier	Accuracy	Precision	Recall	F1-score
Artificial Neural Network (ANN)	98.3%	99.1%	97.7%	98.5%
Support Vector Machine (SVM)	97.1%	97.0%	97.0%	97.0%
Logistic Regression (LR)	60.5%	58.4%	62.2%	59.9%

Table 1 shows the comparison of the performance of different classifiers for cacao pod classification that we used in the experiments. Empirical results reveal that the Artificial Neural Network (ANN) turns out to be superior among the three classifiers tested for performance measures (i.e., accuracy, precision, recall, and f1-score) with 98.3% accuracy in particular. Hence, we employ this model in the development of the system.

3 Results and Discussion

In our experiment, the data acquired had a total number of 217 images of healthy cacao pods and a total number of 201 unhealthy cacao pods. The results had shown that the developed system is capable of extracting Color Histogram Features and Local Binary

Pattern (LBP) Features as input and capable of classifying healthy or unhealthy cacao pods.

Color Histogram represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color space or the set of all possible colors. A total of 768 color histogram features were extracted from the data images. Local Binary Pattern (LBP) feature is a simple and effective texture operator that labels the pixels of an image by thresholding each pixel's neighborhood and treating the result as a binary number. Each cacao pod image has a total texture value of 59.

Figure 8 shows the neural network architecture. The first layer receives the input. The 827 input indicates the number of extracted features. The second layer is the Hidden layer. It receives data from the first layer. There are ten hidden neurons in the hidden layer. The third layer is the output layer. It shows that the 827-input data that we used came up with four output neurons.

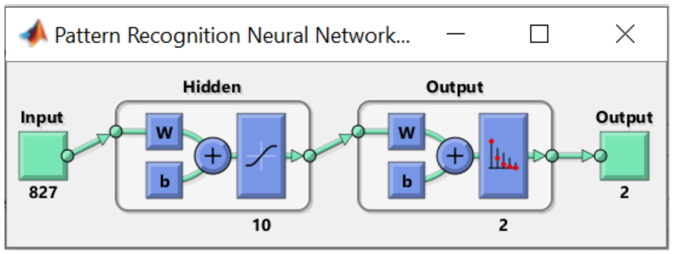

Fig 8. Neural Network Architecture.

These two output neurons represent the target values. The target values are the following: 1 and 0. The binary number 1 represents the Healthy classification while 0 represents the Unhealthy classification of the cacao pod image.

Figure 9 shows the overall performance of the network. The best performance of the network is 0.07255 at epoch 32. After training the network, the weights of the implemented network were acquired.

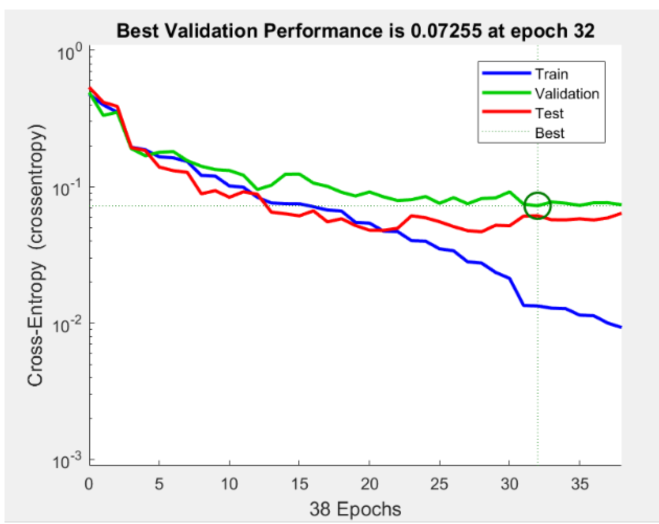

Fig 9. Best Validation Performance

Figure 10 shows the Receiver Operating Characteristic (ROC) of the trained network for classifying healthy and unhealthy cacao pods. It also shows the plotting of the True Positive Rate (TPR) against the False Positive Rate (FPR). This implies that the trained model is considered a good model.

Figure 11 shows the Confusion Matrix of the trained Network. The total number of healthy cacao pod images is 217 and the total number of unhealthy cacao pod images is 201. In this confusion matrix, out of 217 total number healthy cacao pod images, 215 or 51.4% are correctly classified as healthy and only 2 cacao pod image or 0.5% are incorrectly classified as unhealthy. On the other hand, out of 201 total number unhealthy cacao pod images, 196 or 46.9% are correctly classified as unhealthy while 5 images or 1.2 % are incorrectly classified as healthy.

While there have been many similar works related to classification of cacao [8,29], experiments reveal that our approach yields excellent results in terms of the classifier's accuracy of 98.3% as shown in Table 1. Based on the experiments we conducted, our

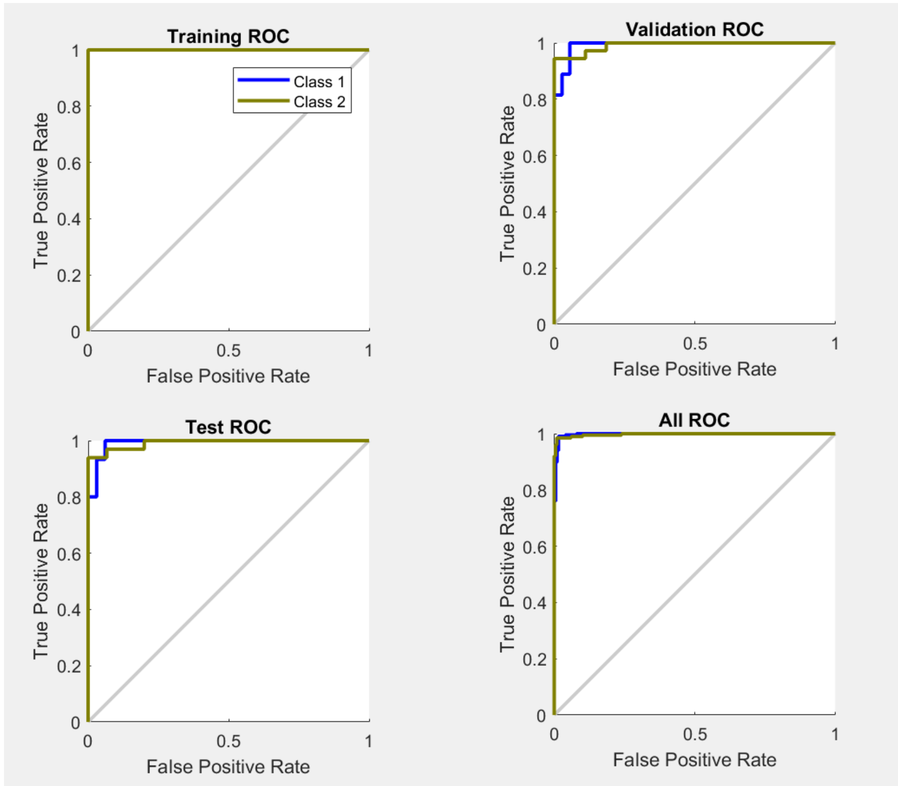

Fig 10. Receiver Operating Characteristic ROC

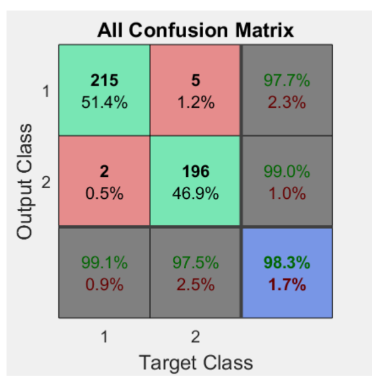

Fig 11. AllConfusion Matrix

study showed that using color histogram and local binary pattern as features, and ANN as classifier, is the best method in classifying healthy and unhealthy cacao pods.

Another advantage of the study is that it does not require descriptive sampling of the pods or required the fruit to be plucked from the tree and opening it. Also, our approach to combine Color Histogram and Local Binary Pattern as features of the classifier is easy to manipulate and fast. Furthermore, the Artificial Neural Network proves to be very efficient and works well based on our experiment.

4 Conclusion

In this study, we introduce an objective approach that performs cacao pods classification (i.e. healthy or unhealthy) that discriminates healthy cacao pods from unhealthy ones using Artificial Neural Network (ANN). Additionally, we were able to successfully extract features from the captured images of cacao pods with the use of Image Processing techniques. A significant amount of dataset was also collected from cacao farms that were used to conduct the training and testing procedures.

The results collected from the training procedure served as the standard for which the further data will be compared to have an accurate classification of healthy and unhealthy cacao pods. We were able to classify healthy and unhealthy cacao pods by analyzing the images captured with 98.3% accuracy.

This study will aid cacao farmers to potentially improve the effectiveness and efficiency of managing the crops especially in classifying cacao pods. This require minimal human interaction thereby making the farmers work faster and with more accuracy during the harvest period. Cacao farmers will also be able to increase their harvest ready for either importation or chocolate processing.

5 Recommendations

The study presented the capability of the Artificial Neural Network (ANN) to classify healthy and unhealthy cacao pods. The accuracy of the system is quite promising however, there are still a lot of rooms to be explored to have the most optimum result and system performance.

With due consideration of the scope and result of this study, the following are recommended for further study.

- Additional Cacao Pod images to be used for training
- Additional Cacao Pod images to be used for testing
- Train data in different environmental set-up to make the system robust

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