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Recognizing Cassava Variety using Artificial Neural Network with Otsu Algorithm for Image Segmentation

Magdalene C. Unajan, Bobby D. Gerardo

Abstract: *One of the many indispensable tools for ensuring a quality product is variety identification. Human experts identify the product variety by personal observation; however, in their absence and rarity, technology can be used instead. This paper proposed to develop a technique that can be used to determine the type of cassava through its digital leaf image. There are 235 images used for testing and preprocessing. Two images for each of the 47 cassava varieties are used in this study. The preprocessing method was performed first before the extraction of features. The Otsu algorithm segments the leaf image from the background. From the leaf samples, nine (9) color features, three (3) morphological features and, three (3) shape features were extracted. The values of the 15 extracted features are the input for the system for variety recognition. Backpropagation method of the artificial neural network (ANN) of multilayer perceptron is used to train the system. For the input, hidden, and output layers, the values are 15, 30, and 47, respectively. These correspond to the 15 extracted features, 30 hidden layers, and 47 cassava varieties. The accuracy obtained in the experiment is 85.11%. It can be concluded that the technology was able to identify the different cassava varieties effectively.*

Index Terms: *artificial intelligence, backpropagation, feature extraction, image segmentation, precision agriculture*

I. INTRODUCTION

Many families all over the world consider Cassava (*Manihot esculenta Crantz*), from the Euphorbiaceous family, as their staple food [1]. Amongst other crops like wheat, rice, maize, potato, and barley, cassava ranks as the sixth most important crop in tropical countries [2]. Some families in Asia, as well as some regions in Latin America with larger fields cultivate their cassava for commercialization purposes while families with smaller plots use cassava for personal consumption [3]. As predicted by [4], [5], [6], [7], [8], the global demand for primary staple food will increase by 60% to 110%. This is a consequence in the rapid rise of global population and increased urbanization [9], [10]. In the Philippines, many institutions and training centers breed different cassava varieties. Each variety of cassava has different quality and characteristics. As a significant crop in the Philippines because of its many uses, there is an increasing demand, not just from families but also industrial partners like feed milling industries. As compared to other ASEAN countries, the supply of cassava in the Philippines remains less competitive and low [11]. High yielding cassava can lead to high production as well. Human experts identify what variety is best planted in what kind of environment as well as what type has the highest yield. Because of this, variety identification assures tuber purity and quality. However, in the absence or the rarity of these experts, technology can be used instead. One example of this technology is image processing with artificial intelligence. A study by [12] also uses technology such as image processing by using digital leaf images for plant recognition. Image processing algorithms, with artificial intelligence like Artificial Neural Network (ANN), commonly go hand-in-hand in research topics. Automated image analysis is an alternative method in some agricultural applications. It has been termed as precision agriculture replacing manual methods and subjective analysis by human experts. These include but does not limit to recognition of plant diseases, pests, and variety identification.

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* Correspondence Author
Magdalene C. Unajan*, Graduate Programs, Technological Institute of the Philippines, Cubao, Quezon City, Philippines.
Bobby D. Gerardo, College of Information and Communications Technology, West Visayas State University, Iloilo City, Philippines.

II. ARCHITECTURE DESIGN AND PROPOSED MECHANISM

The system architecture for the recognition of cassava variety is shown in Fig. 1

A. *Image Acquisition and Image Preprocessing*

Using a cellular phone or a digital camera, the sample leaf images of cassava plants were captured from the PhilRootcrops Research Center in Visayas State University, Visca, Baybay City, Leyte. The preprocessing steps include image resizing, cropping, brightness and contrast adjustment, and minimizing noise. These images were manually identified by a human expert.

B. *Image Segmentation*

The Otsu algorithm separated the region of interest (ROI) of the leaf image from its background. In image processing, segmentation is an essential basic operation for meaningful analysis and interpretation of an acquired image. Segmentation plays an important function as a pre-processing step for further image analysis. This process subdivides an image into segments [13].

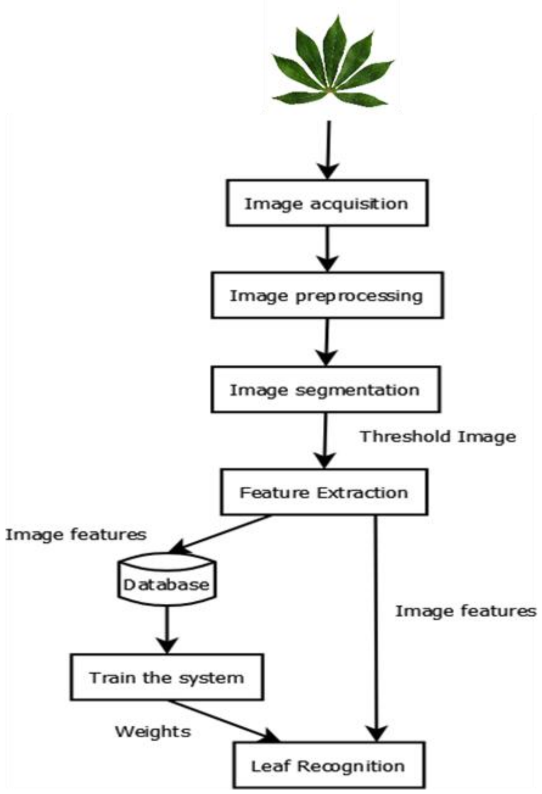


Fig. 1 System architecture of the cassava variety recognizer

Otsu by Otsu Noboyuki is a dynamic threshold selection method [14]. The weighted sum is of the variances in between classes is minimized. These classes refer to the pixels of the foreground and background in order for the minimum threshold to be established. First, the images are partitioned into two classes represented as W_1 and W_2 with T as the gray threshold. The total number of gray levels of the image L are presented as $W_1 = \{0, 1, 2 \ldots, T\}$ and $W_2 = \{T + 1, T + 2, \ldots L-1\}$.

Let n_i and $N = \sum_{i=0}^{L-1} n_i$ be the total number of pixels at a given image where the number of pixels is at at i gray level. Equation (1) defines the probability occurrence of gray level *I*.

$$p_i = \frac{n_i}{N}, \quad p_i \geq 0, \sum_{i=0}^{L-1} p_i = 1 \tag{1}$$

The region of interest represented as two classes W_1 and W_2 corresponds to the foreground and background. The probability for the background of the two classes is in (2).

$$P_{w1} = \sum_{i=0}^{T} p_i \text{ and } P_{w2} = \sum p_i = 1-P_{w1} \tag{2}$$

$$\mu_{w1} = \sum_{i=0}^{T} \frac{i * p_i}{P_{w1}} \tag{3}$$

$$\mu_{w1} = \sum_{i=T+1}^{L-1} \frac{i * p_i}{P_{w2}} \tag{4}$$

Computation for the means of the classes W_1 and W_2 is shown in (3) and (4).

From (3) and (4), the equivalent formula can be obtained:

$$\sigma^2(T) = P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2$$

$$\sigma^2(T) = P_{w1}P_{w2}(\mu_{w1} - \mu_{w2})^2 \tag{5}$$

T* represents the optimal threshold. It is obtained through maximizing the variances of the within-classes.

$$T^* = Arg \max_{0<T<L-1} \sigma^2(T) \tag{6}$$

This simplicity of the method is the reason for the wide usage of Otsu in image segmentation.

C. *Feature extraction*

After image segmentation process, colour, morphological, and texture features are extracted based on [15]. As shown in Fig. 2, the colour features, red, green, and blue, are compared amongst the 47 different varieties. Next is the extraction of morphological features.

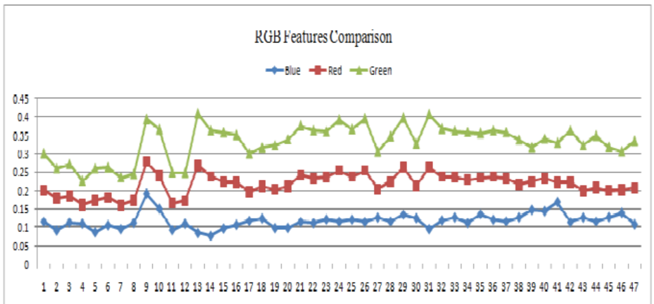


Fig. 2 Comparison of RGB features among 47 cassava varieties

Morphological features of the image refer to geometry related features such as extent, roundness, compactness, and shape. Fig. 3 shows the extracted morphological features of the digital leaf image.Other features extracted are the Hue, Saturation, Value (HSV), shape, and Luminance, Chrominance (LCbCr) features as shown in Fig. 4.

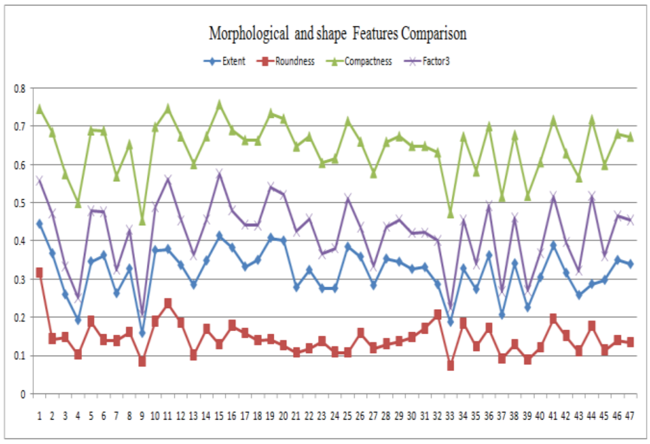
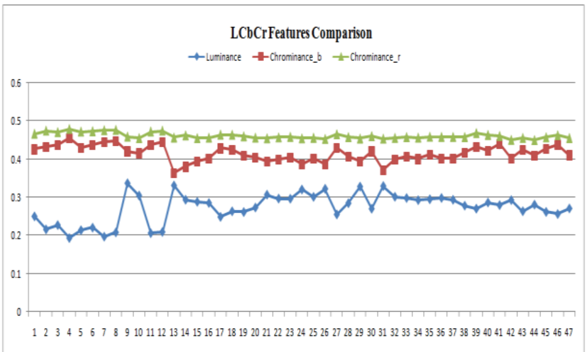


Fig. 3 Comparison of the extracted morphological features of the cassava leaf



The extracted features were considered as input for the neural network in the variety recognition.

D. *Variety recognition*

Values of the extracted features were normalized using (7) to make sure that the values feed into the input layer are between 0 and 1.

$$Normalized\ valueF_i = \frac{ValueF_i - \min(F_i)}{\max(F_i) - \min(F_i)} \quad (7)$$

where: *Fi* corresponds to feature i;

normalized valueF$_i$ – value of feature i after normalization process

value – current value of F_i;

min_{Fi} – is the minimum value F_i;

max_{Fi} – is the maximum value F_i.

The total number of features is 15, and this represents the 15 neurons for the input layer of the artificial neural network (ANN). The 30 neurons correspond to the hidden layer of the ANN. The 47 cassava varieties correspond to the 47-output layer. Fig. 5 shows the ANN architecture of the cassava variety recognizer.

III. RESULTS AND DISCUSSION

The artificial neural network (ANN) was trained using two (2) samples for each of the cassava varieties. The input layer is configured with 15 neurons corresponding to the 15 extracted features. The hidden layer is 30 neurons. The 47 output layers correspond to the total number of cassava varieties which is 47. Different values of the training parameters were tried to obtain the minimum error at an acceptable duration. ANN's system is configured with a momentum of 0.01 with a learning rate of 0.0 and a maximum iteration of 100,000 with a learning rate of 0.0. Fig 6 shows training in progress for the cassava variety recognizer while Fig. 7 shows the recognizer with a recognition a sample recognition result.

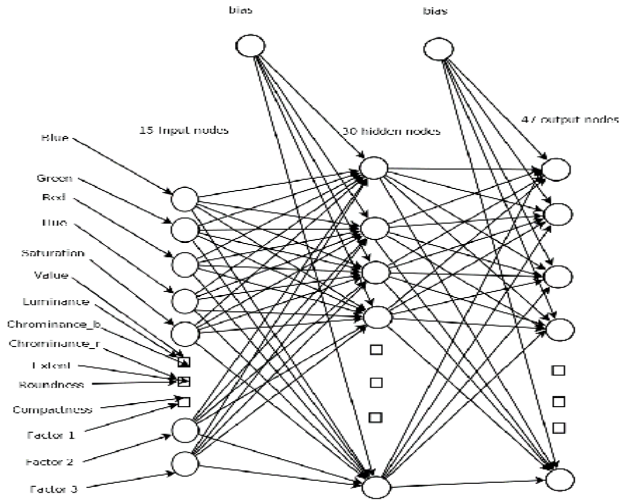


Fig. 5 ANN architecture of the cassava variety recognizer system

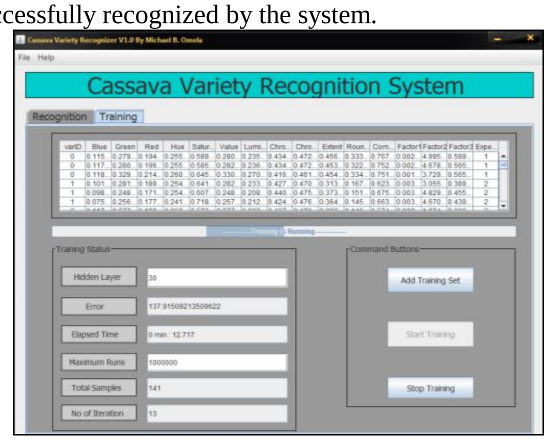
The total number of trained images was two hundred thirty-five (235). Three cassava leaf images per variety were collected to determine the accuracy of the system. (8) shows the formula in determining the accuracy of the variety recognizer.

$$\%accuracy = \left(1 - \frac{total\ sample - total\ recognized}{total\ sample}\right) * 100 \quad (8)$$

where:

total sample - is the total number of test samples

total recognized – is the total number of images successfully recognized by the system.



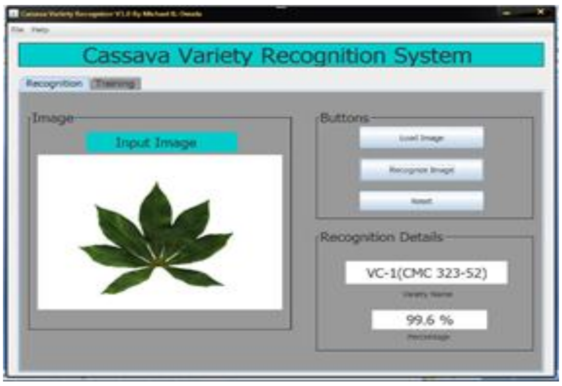


Fig. 6 Cassava variety recognizer while training is in progress

Table 1 shows a sample result of the variety identification. The table shows only 10 results out of the 141 test samples used. The system has successfully recognized 120 test images out of 141 test images used.

Table 1. Cassava variety identification result

Sample No.	Expected Variety	Recognized Variety	Matching Percentage	Remarks
1	NSIC Cv-20(Sultan5)	NSIC Cv-20(Sultan5)	99.80%	Correct
2	NSIC Cv-20(Sultan5)	NSIC Cv-20(Sultan5)	98.94%	Correct
3	NSIC Cv-20(Sultan5)	PSB Cv-19 (SM 808-1)	95.56%	Wrong
4	NSIC Cv-21 (LSU Cv-10)	NSIC Cv-21(LSU Cv-10)	99.07%	Correct
5	NSIC Cv-21 (LSU Cv-10)	NSIC Cv-21(LSU Cv-10)	99.64%	Correct
6	NSIC Cv-21 (LSU Cv-10)	NSIC Cv-21(LSU Cv-10)	99.25%	Correct
7	NSIC Cv-22 (LSU Cv-11)	NSIC Cv-29(Rajah1)	10.72	Wrong
8	NSIC Cv-22 (LSU Cv-11)	NSIC Cv-22 (LSU CV-11)	85.45%	Correct
9	NSIC Cv-22 (LSU Cv-11)	NSIC Cv-22 (LSU Cv-11)	0.93%	Wrong
10	NSIC Cv-23 (LSU Cv-12)	NSIC Cv-23 (LSU Cv-11)	76.39%	Correct

Some testing samples were not accurately recognized due to the similarities of features in other variety especially color and shape. This result implies that there is a need to look for other features that could distinguish these very similar varieties.

IV. CONCLUSION AND RECOMMENDATIONS

This study has developed a system for cassava variety recognition. The system has obtained an accuracy rate of 85.11%. This result implies that the system can correctly identify the different cassava varieties in the test images sample. It implemented the Otsu algorithm for the image segmentation as part of the preprocessing steps in the image analysis. Image processing techniques for feature extraction were also used for image analysis. The extraction of color, morphological, and shape features of the digital image is based on the study of [15]. The system learns using a backpropagation algorithm based on the artificial neural network. The inputs for the ANN are 15 input nodes for the 15 extracted features; 30 hidden nodes; and, 47 output nodes to correspond to the 47 different cassava varieties used in this study. Further studies could increase the accuracy rate of the system. Improving the accuracy of the cassava recognizer could be achieved by increasing the nodes in the hidden layer. Also, it could be possible to increase the maximum iterations of the training. Adding more features such as moments for shape classification would also improve the efficiency of the system aside from adding more training images for each of the cassava variety. The segmentation result of the digital images can also be improved using a modified Otsu-based image segmentation (OBISA). This study could also be implemented to work on a mobile platform to enhance the usability and accessibility of this system.

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AUTHORS PROFILE

Magdalene C. Unajan is an Assistant Professor at the Visayas State University, Visca, Baybay City, Leyte. She obtained her BS in Information Technology on 2003 at the Cebu Institute of Technology – University (CIT-U), Cebu City. From the same university, CIT-U, she finished her Master in Information Technology on 2003. She is currently in her dissertation writing for the degree in Doctor in Information Technology at the Technological Institute of the Philippines, Cubao, Quezon City. Her research interest includes but not limited to image processing, artificial intelligence, web development and database management.

Bobby D. Gerardo is a professor from the College of Information and Communications Technology, West Visayas State University, Iloilo City. His field of specialization and research is on Distributed Systems, Data Mining, Telematics, Location Based Services, IT and Data Security. He is also affiliated in the Graduate Programs of Technological Institute of the Philippines, Cubao, Quezon City, Philippines.