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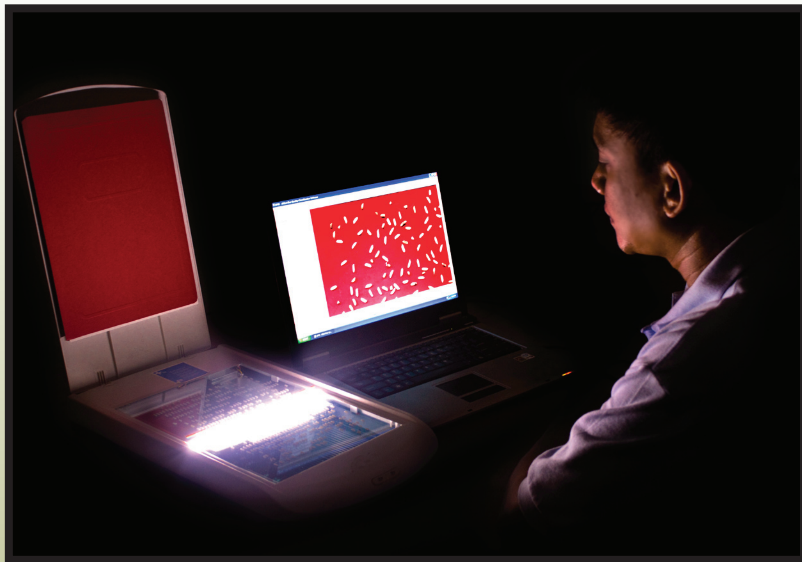

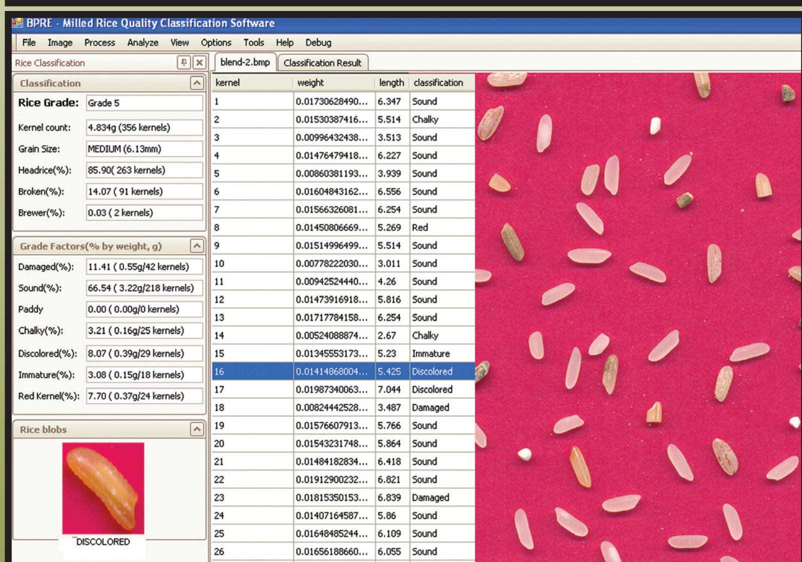


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Philippine Center for Postharvest Development and Mechanization
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# Development of a Computer Vision System for Milled Rice Quality Analysis

Manolito C. Bulaong, PhD. and Oliver C. Agustin, PhD.[1]

## ABSTRACT

The computer vision system (CVS) was developed as an alternative to the tedious, subjective, and slow method of manual milled rice analysis. It is composed of a document scanner and a computer with image-processing software. The scanner acquires the image of a milled rice sample and the computer predicts quality parameters such as weight, size, percent of headrice, brokens, brewers, and defective grains. It also gives the grade of the sample based on the existing Philippine Grain Quality Standards. Several computer models were built as part of the image processing software including weight prediction, size measurement, and color-related quality classification.

The weight prediction model gave a correlation coefficient of 0.98 with projected area of the grain.. The model to predict the percent by weight of headrice, brokens, and brewers gave an overall accuracy of 99 percent. A model using the artificial neural network (ANN) predicted six milled rice quality parameters with coefficient of multiple determination (R2) of 0.97 for sound, 0.73 for damaged, 0.94 for chalky/immature, 0.96 for discolored, 0.94 for red kernels, and 0.92 for paddy using the test set of images. Based on speed, accuracy and repeatability tests, the CVS performed better than manual method of analysis.

## INTRODUCTION

### Rationale

Aside from milling degree and moisture content, milled rice quality classification is determined by the amount of head rice, broken grains, brewers, defectives, and foreign matter present in a sample. At the NFA, trained classifiers visually inspect each grain and based on its size and color characteristics, each grain is separated into each quality classification and the amount of each class presented on a percentage weight basis. This manner of analysis is subjective, tedious and slow. The result is affected by the skill of the classifier, time of day and working conditions. Complete analysis of each sample takes more than an hour and costs P550 per sample (NFA, 1998). Development of a computer vision system (CVS) for milled rice quality analysis will ensure objective, accurate and fast results and will modernize the existing method being used by the grain industry.

### Analysis of the Problem

Milled rice quality analysis is done on the basis of size and color of the grain. Each grain is visually inspected and separated into size-related components (headrice, broken and brewers) and color-related components that distinguish sound grains from defective

[1] *Dr. Oliver C. Agustin of Vera Equinox Technologies developed the image processing software used in the project.*

grains (damaged, discolored, chalky, red kernels, paddy). Each grain has its own shape and color characteristics, which allow a trained classifier to separate each grain according to its own quality classification. A CVS can be used to extract the shape, and color characteristics from each grain and correlate them into grain quality. In this study, the weight and shape-related characteristics of each grain were correlated with size-related classification, while the color patterns of each grain were correlated with color-related classification. The size-related models were built using linear regression equations. The color related model, which is difficult to build using statistical methods, was built by extracting the color patterns from each grain and using an artificial neural network (ANN) to predict the quality. The ANN mimics the brain's own problem solving process. Just as humans apply knowledge gained from past experience to new problems or situations, a neural network takes previously solved examples to build a system of "neurons" that makes new decisions, classifications, and forecasts. Neural networks look for patterns in training sets of data, learn these patterns, and develop the ability to correctly classify new patterns. By training the ANN to recognize color patterns of each grain, it could classify each grain into color-related quality components.

## OBJECTIVES

General: To develop a computer vision system for determination of physical quality of milled rice.

Specific:

1. To develop image processing algorithms to isolate grain images from background and extract shape and color features related to milled rice quality,
2. To develop a computer model for predicting weight and size of milled rice grains,
3. To develop a computer model for predicting color-related quality of milled rice using the color signatures extracted from milled rice images,
4. To compare the speed, accuracy and repeatability of the developed computer vision system with the results of human inspection.

## REVIEW OF LITERATURE

Technology advances enabled computers to recognize shapes, colors, and textures of object simulating human vision. A CVS consists of an image acquisition system which serves as the "eye" and a computer equipped with image processing and analysis software which serves as the "brain". This technology is now being utilized for food quality assurance and classification.

Advantages of using CVS include: quick and objective measurement, cost-effective, accurate, non-destructive, consistent results, and reduced tedious human involvement (Brosnan & Sun 2004).

Most CVS in literatures used expensive charge coupled device (CCD) cameras for image acquisition. Although the performance of CCD cameras has been satisfactory, their cost and maintenance are prohibitive. It also requires an imaging chamber with precision-controlled lighting conditions, adding further to the cost of the system. The use of an ordinary document scanner for CVS as an alternative to expensive digital cameras yielded promising results for cereal grains such as corn, peas, and wheat (Shahin et al. ,2004, Paliwal et al.,2003, and Bulaong et. al., 2005). Document scanners cost less than one-tenth of high-end color CCD cameras and does not require precision-controlled lighting conditions.

For milled rice application, however, the grains should be presented in a non-touching fashion as individual analysis of each grain is required. Manually placing each grain on the scanner glass surface in non-touching fashion is tedious and slow. Digital separation of touching grains would be easier and faster. Several authors have developed algorithms for digital separation of grain images (Shatadal et al.,1995a, Casasent et al., 2001, Zhang et al., 2002, Yun et al., 2002, Shahin et al.,2004, Wang & Chou, 2004) but their application for milled rice needs further exploration.

## CONCEPTUAL FRAMEWORK

Computer vision systems simulate human vision by electronically acquiring and recognizing an image of an object. Existing milled rice quality analysis employs human vision to separate each grain into each quality group to arrive at a specific classification. In the developed computer vision system, a document scanner acts as the “eye” of the system. The computer, using an image processing software developed in-house, acts as the “brain” of the system. The image is processed to extract the shape and color patterns from each grain. A computer model was developed to recognize the shape and color patterns of each grain and predict the grain physical characteristics (headrice, brokens, brewers, sound, and defectives) to arrive at a specific grain classification. The conceptual framework is illustrated in Figure 1.

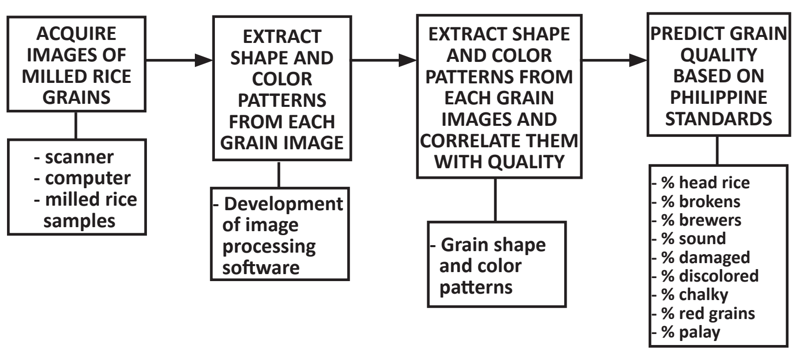



**Figure 1.** Conceptual framework for the proposed computer vision system for milled rice quality analysis

## METHODOLOGY

### Steps in Milled Rice Quality Analysis Using Machine Vision

Milled rice quality analysis using computer vision consists of the steps as shown in Figure 2. Step 1 is image acquisition to capture milled-rice image using a camera or scanner. In step 2, the image is pre-processed by filtering out noise and eliminating background color. Step 3 extracts all grain images (also called blobs) and separate them into individual grain images. In step 4, various shape and color features are extracted from each grain image. Weight is predicted in step 5 using a computer model correlating weight to shape features of the grain. Shape and color features are processed in step 6 to obtain the classification of each rice image into each quality group. Finally, the resulting classification of milled rice kernels is summarized and used to draw quality evaluation based on the limits specified by the Philippine Grain Quality Standards.

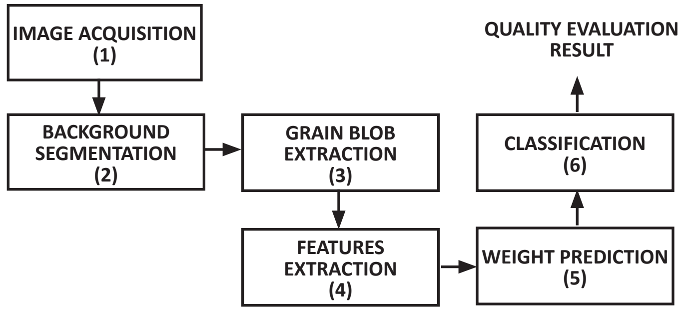



**Figure 2.** Steps in milled rice quality evaluation using CVS

In this study, the development of the CVS consisted of three main tasks – assembly and calibration of the CVS hardware, development of the image processing software, and preparation of milled rice samples for imaging (Figure 3). The CVS hardware consisted mainly of the image acquisition device (a document scanner) and the computer. The image processing software requires the development of several algorithms to execute the various steps enumerated in Figure 2. Commercially available milled rice samples were prepared for image acquisition representative of the various quality classification enumerated in the Philippine Grains Quality Standard.

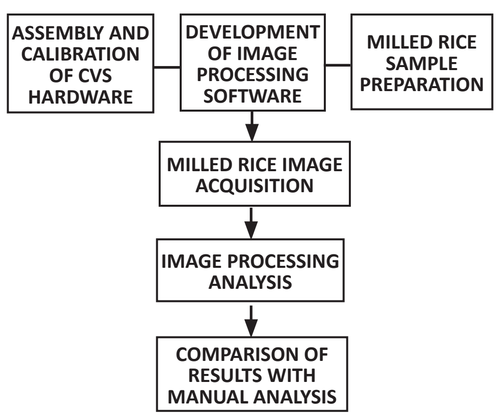



**Figure 3.** Summary of activities conducted in the study

### A. Assembly and calibration of CVS hardware

A low-cost version of the CVS hardware was assembled consisting of a flatbed document scanner (HP scanjet 2400) as the image acquisition device and a desktop computer (Pentium 4, 2.13 Ghz processor, 512mb RAM, 200Gb hard disk) for image processing (Figure 4). Milled rice samples is poured on the scanner glass surface and spread in a single layer. A red-colored cartolina was pasted in the inside surface of the scanner cover to serve as background for the image. The choice of red color background was established in previous experiments as discussed later. After replacing the cover, an image of the milled rice sample is scanned and transmitted to a desktop computer via a USB cable. The scanner was color calibrated using a standard color reference tile (Minolta reflector tile with a color value of Y = 87.4, x = 0.313, and y = 0.330 under D65 light source). Red, green, and blue (RGB) values of the reference color were taken at regular intervals and checked for any shift in color and illumination. The automatic settings of exposure, color balance, and contrast of the scanner were set to manual. This is to eliminate variability in image quality.

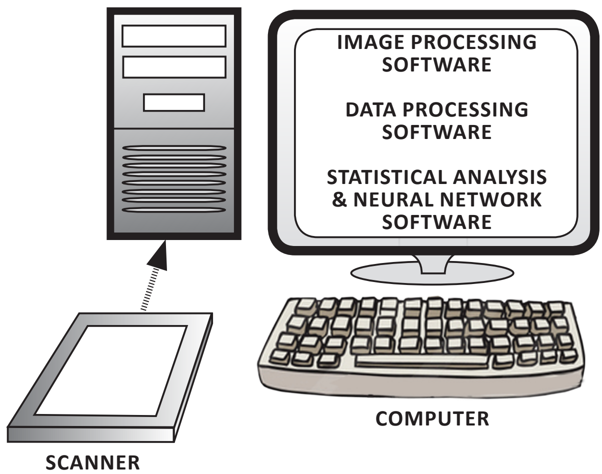



**Figure 4.** Schematic diagram of the computer vision system using a flatbed scanner as image acquisition device and a computer to process the image.

### B. Development of image processing software

The design of image processing software includes the development of the following algorithms:

1. Development of a windows-based graphical user interface (GUI) for execution of developed algorithms;
2. Control of imaging hardware through a computer including image acquisition and storage;
3. Segmentation to filter out noise and remove background color from grain image;
4. Digital separation of touching grain images;
5. Extraction of morphological and color features from each grain image;
6. Development of model to estimate weight of samples;

7. Measurement of grain size and computation of percentage by weight of head rice, broken grains, and brewers;
8. Development of model to classify milled rice according to sound grains and defectives using artificial neural network; and the
9. Integration of developed algorithms into an image processing software.

*Development of a windows-based graphical user interface (GUI)*

The GUI allows user-friendly execution of the developed algorithms. It is windows-based with drop down menus for various operations. The GUI was developed using C++ programming language by Dr. Oliver Agustin of Vera Equinox Technologies.

*Control of imaging hardware*

The control of the imaging hardware involves scanning and saving of grain image from the scanner to the computer hard disk via the GUI.

*Segmentation to separate grain image from background*

Background color needs to be separated from the grain image to allow spatial and color measurements to be done on grain image only. Best background separation is achieved when there is maximum contrast between background and grain color. Two color models were tested, the RGB and the CIE L*a*b* color model. The color model which could eliminate background color without affecting grain color was chosen.

*Digital separation of touching grain images*

Grain separation is necessary to allow spatial measurements for each grain. Placing the grain in the scanner in a non-touching fashion is a tedious process and several authors attempted to design automatic presentation systems with limited success (Casady et.al., 1989, Jayas, 1999, Wan, 2002, Yun, 2002). Digital separation was employed in this study using the watershed algorithm described by Vincent and Soille, 1991. The steps involved in digital separation of touching grain images are illustrated in Figure 5. The original image is converted into a binary image. Each grain image was eroded and dilated twice to remove noise and unwanted objects in the image. The object boundary is determined using the watershed algorithm. The grain image is then separated into individual blobs prior to feature extraction.

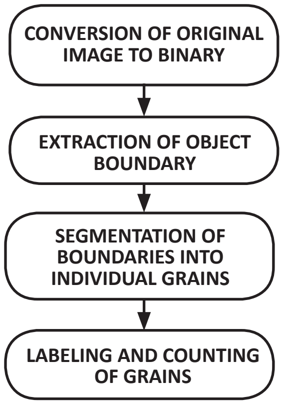



**Figure 5.** Algorithm for digital separation of touching grain images

*<u>Extraction of morphological and color features from each grain image</u>*

Extraction of morphological and color features were done on individual grain image. Morphological features extracted include length, diameter, area, roundness and perimeter for correlation with grain weight and grain size. Color features extracted consist of basic statistics from the RGB and CIE L*a*b* components such as statistical range, mean, and standard deviation as listed in Table 1.

**Table 1**. Color features extracted from each grain image

| | | | | | |
|---|---|---|---|---|---|
| RedRange | GreenRange | BlueRange | LRange | aRange | bRange |
| RedMean | GreenMean | BlueMean | LMean | aMean | bMean |
| RedStdDev | GreenStdDev | BlueStdDev | LStdDev | aStdDev | bStdDev |
| RedMedian | GreenMedian | BlueMedian | LMedian | aMedian | bMedian |

Description of Color Features

Statistical Range (R) – Difference between the maximum and minimum value of an image histogram.

$$R = \max(x) - \min(x) \qquad (1)$$

Mean (μ) – Sum of all pixel intensity values divided by the total number of pixels.

$$\mathrm{m} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{M} f_{i,j} \qquad (2)$$

Standard Deviation (σ) – a measure of variability which defines how spread the pixel intensities around the mean.

$$\mathrm{s} = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(f_{i,j} - \mathrm{m})^2} \qquad (3)$$

Median – pixel value with the highest number of occurrences.

$$Median = x_{(N+1)/2} \qquad (4)$$

Equations (1), (2), (3), and (4) are used to calculate image statistics from each component of RGB and CIE L*a*b color spaces providing a total of 24 color features.

*Development of model for weight estimation of milled rice grain*

Weight measurements of 341 grain samples having different sizes, shapes, and belonging to different rice defectives categories were taken using a three-decimal digital balance (Metler model HR-120). The same grains were imaged individually and morphological features composed of length, diameter, area, roundness and perimeter were extracted from each grain image. Each morphological feature was correlated to weight using linear regression equation:

$$K(Ai) = c_1 A_i + c_2 \qquad Ai > 1 \qquad (5)$$

In the above equation, K(Ai) is the weight of ith rice kernel in grams and Ai is the morphological feature of the ith blob and c1 and c2 are constants based on morphological features used.

*Development of model for measurement of grain size and computation of percentage weight of headrice, broken rice, and brewers*

Grain classification according to size was based on the NFA standards (NFA 2002) as follows:

- Short grain – rice with 80 percent or more of the whole milled rice kernels having a length of less than 5.5 mm
- Medium grain - rice with 80 percent or more of whole milled rice kernels having a length of 5.5 to 6.3 mm
- Long grain – rice with 80 percent or more of whole milled rice kernels having a length of 6.4 to 7.4 mm
- Very long grain - rice with 80 percent or more of whole milled rice kernels having a length of 7.5 mm and above
- Headrice – pieces of kernels with ¾ or more of the average length of the unbroken kernel
- Broken kernels – pieces of kernels smaller than ¾ of the average length of the unbroken kernel
- Brewers – small pieces or particles of kernels that pass through a sieve having round perforations 1.4 mm in diameter. This is also known as “binlid” or chips

Length measurement was based on the longest axis extracted from projected grain blobs digitally separated from previous steps. Based on the existing rice quality standards, average grain size, lave is the average length of the top 80 percent of the sorted kernels from longest to shortest in rice sample, R. KH(Ai), KB(Ai), and KW(Ai) is the sum of blob weight of headrice, broken kernels and brewers, respectively, where

$$l_{ave} = \frac{1}{N}\sum_{i=1}^{N} K(L_i), \quad L_S \le L \ge L_{VL} \tag{6}$$

$$K_H = \sum_{i=1}^{N} K(A_i), \quad K(A_i) \ge l_{ave} \tag{7}$$

$$K_B = \sum_{i=1}^{N} K(A_i), \quad K(A_i) \le 0.75 l_{ave} \tag{8}$$

$$K_W = \sum_{i=1}^{N} K(A_i), \quad L_i \le 1.40mm \tag{9}$$

Li refers to the length of ith rice kernel, LS is the minimum length of short rice kernel (~5mm), LVL the maximum length of very long rice kernel (~8mm). The function  is the regression equation for weight estimation as discussed in previous section.

*Development of model to classify milled rice according to sound and defectives category*

A general regression neural network (GRNN) model consisting of 24 inputs (corresponding to 24 color statistics of each grain image) and 7 outputs (corresponding to 7 defectives categories) was built using Neuroshell 2 (Ward Systems). The total dataset is 23,228 rice images extracted from NFA samples. Dataset were randomly sampled, 75 percent for training, 20 percent for calibration, and the remaining 5 percent set aside for testing the accuracy of the classifier. Grains were categorized into sound and five defective categories composed of damaged, chalky/immature, discolored, red kernels, and paddy. Training was automatically stopped after 20 model generations with no improvement of 1 percent in the ANN model was achieved.

*Integration of developed model to image processing software*

All the algorithms developed above were integrated in the GUI using C++ software.

**C. Milled rice samples preparation**

Representative milled rice samples were prepared for imaging consisting of size-related classification (head rice, brokens, brewers, and color related classification (sound, damaged, discolored, chalky, immature, red kernel, paddy). The following description of color-related classification was based on the Philippine Grain Quality Standards (NFA, 2002):

1. Damaged – Kernels which are obviously damaged by insects, water, diseases or any other means as seen by the naked eye
2. Discolored – Kernels that have changed their original color as a result of heating

and other means. This is also known as yellow kernels or fermented kernels

3. Chalky – Kernels whole or broken of which one-half or more is white like the color of white chalk and is brittle upon removal of the hull
4. Immature – Kernels whole or broken which are light-green and chalky with soft texture
5. Red kernel – Kernels that have red bran covering, wholly or partly
6. Paddy – unhulled grain of *Oryza sativa*
7. Sound grains – kernels without any color-related defects as defined above

Representative milled rice samples classified into short, medium, long, and very long were sourced out from Philrice. Each sample were subdivided into 10 grams sub-samples for imaging. Samples of milled rice grains containing varying amounts of headrice, brokens, brewers, sound grains and defectives listed above were taken from NFA central office. Said samples were brought to the Laboratory Services Division of the Technology Resource Development Department (NFA-TRDD) for analysis. Trained NFA classifiers separated each grain according to various size categories (head rice, brokens, brewers) and sound and defective categories (chalky, immature, damaged, discolored, red kernels, and paddy). The classified grains were placed in sealed plastic bags prior to imaging.

**Comparison of CVS with Manually Analyzed Samples**

The CVS output was compared with manually analyzed samples to evaluate its accuracy, repeatability, and speed. Manually analyzed samples from the project “Assessment of the State and Magnitude of Paddy Grains Post Production Losses in Major Rice Production Area” were used for evaluation. The parameters used for comparison consist of weight prediction, size prediction (head rice, broken rice, brewers), and prediction of color-related quality (sound, damaged, chalky, immature, discolored, red, paddy). Forty nine (49) samples were used for weight and size prediction, while ninety eight (98) samples where used for prediction of defectives. Actual length was measured using a standard caliper and actual weight was obtained using a three-decimal digital balance (Metler model HR-120). All samples were scanned three times in a non-touching fashion using the document scanner with mixing in-between scanning intervals. Coefficient of variation was computed among replicates of manually analyzed samples and replicates of the CVS to compare the repeatability of both systems. Number of samples processed per time interval was recorded to evaluate the speed of analysis.

## RESULTS AND DISCUSSION

### Description of Developed Imaging Hardware

The prototype CVS set-up composed of a flatbed scanner and desktop computer is shown in Figure 6. Milled rice samples weighing about 10 grams are spread in single layer fashion on the glass surface of the scanner. A 7 x 9 inches image area of the grain is acquired at 200 dots per inch resolution and saved as uncompressed bitmap file. The scanner automatic exposure and color settings were set to manual to ensure consistent readings. A color tile was used to calibrate the color values of the acquired image. Image acquisition and analysis is executed through the developed image processing software.

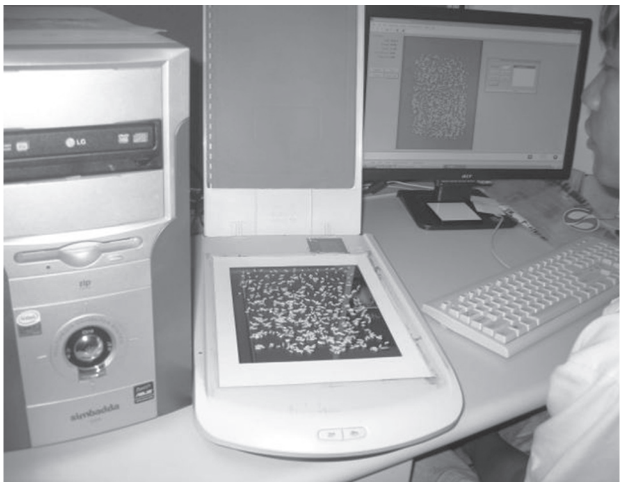


**Figure 6.** The prototype computer vision system consisting of a flatbed scanner (a) as the image acquisition device and a desktop computer (b)

### Description of the Developed Image Processing Software

Figure 7 shows the main menu of the graphical user interface (GUI) of the BPRE Milled Rice Quality Classification Software. It shows the acquired image of milled rice and the individual grain classification data. The left portion shows the summary of the classification parameters which include rice grade, kernel count and weight, size (short, medium, long, or very long), percentage by weight of headrice, broken rice, and brewers, and percentage by weight of sound and defectives (damaged, chalky, discolored, immature, paddy, and red kernels). At the lowest left portion is a preview of the highlighted grain image and its corresponding classification.

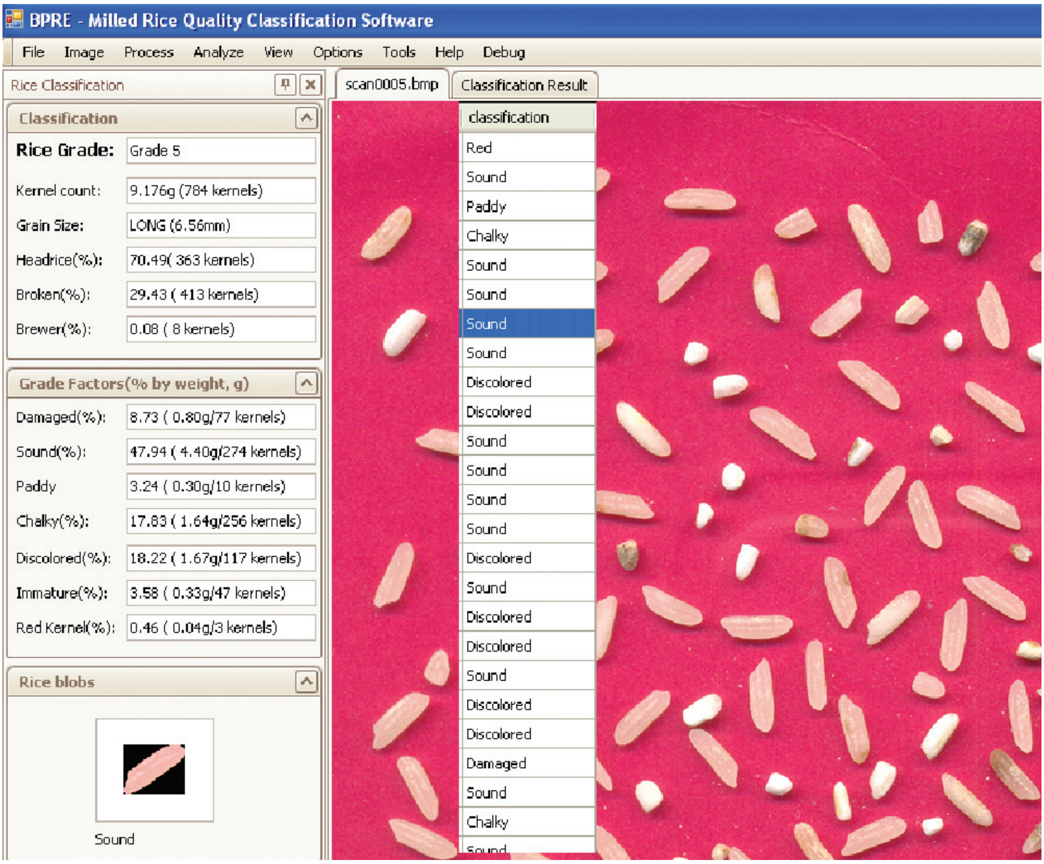



**Figure 7.** The graphical user interface (GUI) of the BPRE Milled Rice Quality Classification Software

## Performance of Image Processing Algorithms

During image processing, milled rice image undergoes several processing steps including background segmentation, digital separation of touching grain images, extraction of individual grain images also called blobs, and extraction of shape and color features. The performance of each algorithm is discussed below:

**a. Background Segmentation** - removes the background color so that it is not included in the analysis. The CIE L*a*b* color model gave a better segmentation result than the RGB model as shown in Figure 8. Some of the color features like grain with dark spots (in red circles) were segmented (converted to background color) in RGB model (Figure 8a). Using the CIE L*a*b* model, all color features in the grain are preserved (Figure 8b).

The amount of filtering or threshold value can be adjusted through a slider bar for each color channel (Figure 9a). In case of milled rice, an *a value of 160 resulted to maximum separation of the red background from the grain images (Figure 9b). Red background was found to have the highest contrast with grain without overlapping with the grain color. Black background was actually the first choice but some damaged grains with dark colors were segmented during the segmentation process.

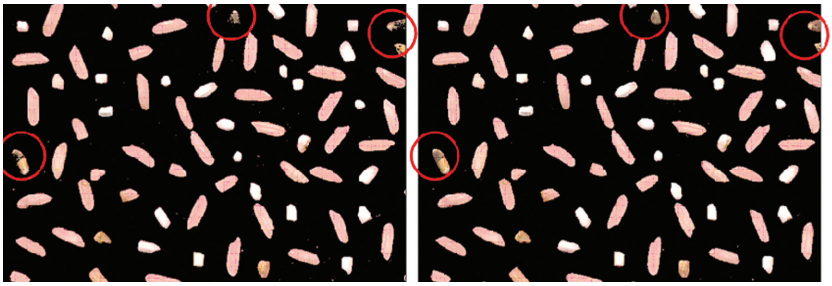


**Figure 8**. Comparison of RGB background (a) and CIE L*a*b*  background (b) showing some segmented grain in the RGB model (red circles) and preserved in CIE L*a*b*

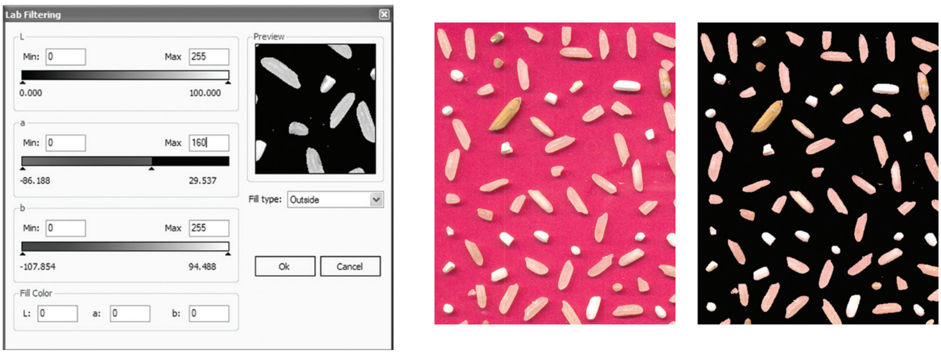
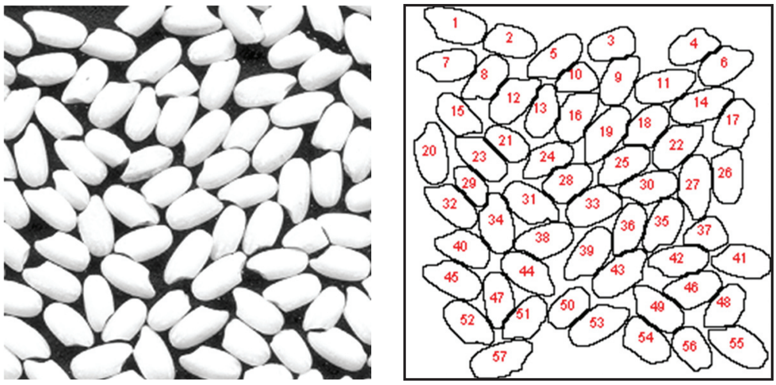



**Figure 9.**  The GUI for background segmentation (a) and the milled rice image before and after background segmentation (b)

**b. Digital separation** – digitally separates touching grain images prior to size and shape measurements using watershed algorithm. A morphological image processing algorithm based on watershed segmentation (Vincent and Soille, 1992) on a binary image was implemented.  Watershed algorithm worked 100 percent in segmenting short grains (Figure 10) but not very efficient for medium to long milled rice kernels (Figure 11).  Some of the touching grains remained clustered while some individual grain was cut into half.  This is a main concern as placing the grains in non-touching fashion on the scanner glass surface is tedious and slow (average of 33 minutes per 10 gram sample) and will lessen the advantage of the CVS being a faster alternative to manual analysis.



**Original image** **Image after watershed and labeling**

**Figure 10.** Image of short grain milled rice before and after digital separation process showing 100% separation.

**Original image** **Image after watershed and labeling**

**Figure 11.** Image of medium grain milled rice before and after digital separation process showing some grains incorrectly separated

**c. Grain Blob Extraction** – this algorithm was developed to enable extraction of segmented grain images also called blobs from the original image. Color blob extraction algorithm made way to extracting morphological and color properties of each segmented kernel. A filter algorithm was implemented to eliminate dust and noise from the extracted blobs. The algorithm was successful in extracting grain blobs from the main image. Samples of extracted kernel blobs are shown in Figure 12. Another algorithm was developed to label each extracted blob for reference.

**Figure 12.** Extracted milled rice kernel color blobs

**d. Extraction of shape and color features** – this algorithm extracted shape and color features from each grain blob. The shape features include perimeter, area, circularity, ferret diameter, and length of major and minor axis. Five shape features and twenty four color features consisting of statistics from the RGB and CIEL*a*b* were successfully extracted from each grain blob. The shape features determine the percentage by weight of headrice, brokens, and brewers and the classification into short, medium, long, and very long grains. The color features were used as input for training the ANN for prediction of color-related quality parameters (sound, damaged, discolored, etc.). The developed algorithm successfully extracted all the shape and color features from each grain image and stored in a spreadsheet file.

**Performance of Weight and Size Prediction Model**

**A. Weight Prediction model**

Of all the shape features evaluated, the projected grain area gave the highest correlation with weight using the linear regression equation

$$W = 0.0015A$$

where A is the projected area of the grain in square mm and W is the predicted weight in grams. A correlation coefficient of 0.9836 was obtained. Figure 13 is the comparison of predicted versus actual weight of milled rice grains.

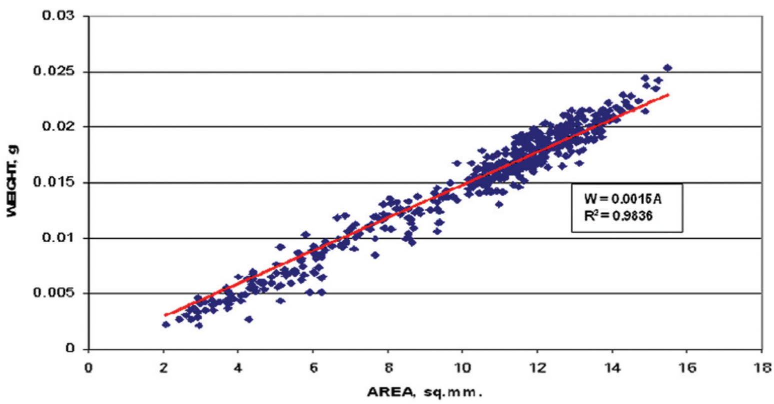



**Figure 13.** Comparison of predicted and actual weight of milled rice grains based on projected area

The model was tested using 49 batches of milled rice samples with weights ranging from 0.1 to 10.0 grams. Table 2 shows the coefficient of determination between the actual and predicted weight of 49 samples with an R2 value of 0.9836 indicating a high level of accuracy for predicting the weight of milled rice.

**Table 2.** Correlation coefficient for prediction of weight using the CVS

| | |
|---|---|
| R-squared | 0.9836 |
| mean square error | 0.1659 |
| mean absolute error | 0.3548 |
| minimum abs error | 0.0070 |
| max abs error | 0.6840 |

*Samples processed: 49 batches*

**B. Prediction of head rice, broken rice, and brewers**

Table 3 shows the comparison of accuracies obtained for percentage by weight of head rice, broken rice, and brewers between manually analyzed and CVS methods. The CVS obtained more than 99 percent accuracy when verified using a caliper. For manual method, headrice measurement was 99.13 percent accurate, broken rice measurement was 75.9 percent accurate and brewers was 100 percent. The lower accuracy for broken rice in manual analysis can be attributed to the error in estimating the boundary between headrice and brokens. Broken rice is defined as grains with less than 3/4 of the length of whole grain. Unless a caliper is used, deciding visually whether a grain is more than or less than 3/4 of length is difficult and very subjective especially when the length of the grain is close to this value. Thus, the CVS measurement is more objective and accurate.

**Table 3.** Comparison of accuracies obtained between manual method and CVS for

| | MANUAL METHOD | CVS |
|---|---|---|
| Head Rice | 99.13% | 0.1659 |
| Broken Rice | 75.90% | 0.3548 |
| Brewers | 100% | 0.0070 |

*Samples processed: 49 batches*

classification of size

**Performance of ANN for Prediction of Color Related Qualities**

Table 4 shows the performance of the generalized regression neural net (GRNN) of Neuroshell 2 for predicting seven color-related quality parameters from test samples. The quality parameters of sound, discolored, red, and palay gave R-squares ranging from 0.92 to 0.97 indicating higher prediction performance than the rest. The damaged category has a lower R-square probably because of its broad characteristics which involves damage by insects, water, and diseases resulting to a wide and varied color pattern. This makes it harder for the ANN to recognize the color pattern. Addition of other patterns such as texture features might increase the recognition capability of the ANN for damaged category. The immature category gave the lowest R-square of 0.48 probably because of its similar characteristics with chalky (R-square of 0.88) resulting to overlapping color patterns. This was proven true when the patterns from the chalky and immature were combined and the ANN was re-trained resulting to a higher R-square of 0.94 (Table 5).

The performance of ANN was further improved when the ANN was re-trained with defective categories (except paddy) combined together resulting to R-squares of 0.97 for sound, 0.97 for defectives, and 0.98 for palay.

**Table 4.** Performance of the generalized regression neural network for seven quality categories using 1,161 test samples

| Output | Sound | Damaged | Discolored | Chalky | Immature | Red | Palay |
|---|---|---|---|---|---|---|---|
| R-squared | 0.9687 | 0.7277 | 0.9498 | 0.8783 | 0.4768 | 0.9315 | 0.9201 |
| Mean square error | 0.004 | 0.02 | 0.007 | 0.026 | 0.036 | 0.009 | 0.004 |
| Mean absolute error | 0.011 | 0.034 | 0.018 | 0.053 | 0.067 | 0.024 | 0.005 |
| Min. absolute error | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Max. absolute error | 0.989 | 0.998 | 0.998 | 1 | 1 | 0.932 | 0.957 |

**Table 5.** Performance of the generalized regression neural network for six quality categories using 1,161 test samples

| Output | Sound | Damaged | Discolored | Chalky/Imm | Red | Palay |
|---|---|---|---|---|---|---|
| R-squared | 0.9718 | 0.7378 | 0.9653 | 0.9394 | 0.9446 | 0.9193 |
| Mean square error | 0.004 | 0.015 | 0.005 | 0.014 | 0.008 | 0.003 |
| Mean absolute error | 0.009 | 0.026 | 0.013 | 0.023 | 0.017 | 0.004 |
| Min. absolute error | 0 | 0 | 0 | 0 | 0 | 0 |
| Max. absolute error | 0.997 | 1 | 0.847 | 1 | 1 | 1 |

**Table 6.** Performance of the generalized regression neural network for three quality categories using 1,161 test samples

| Output | Sound | Defectives | Palay |
|---|---|---|---|
| R-squared | 0.9704 | 0.9712 | 0.9841 |
| Mean square error | 0.004 | 0.005 | 0.001 |
| Mean absolute error | 0.009 | 0.011 | 0.002 |
| Min. absolute error | 0 | 0 | 0 |
| Max. absolute error | 0.999 | 0.999 | 0.704 |

*Defectives are damaged, discolored, chalky, immature, and red kernels combined together*

### Average Processing Time Using the CVS

Grain placement on the scanner glass consumed the largest amount of time (average of 33 minutes per 10 gram sample) as the digital separation algorithm was not working efficiently for medium and long grains. When samples were placed in touching fashion, it took an average of less than two minutes per 10 grams sample. Computer time for image acquisition, processing, and grain classification took less than one minute. If the performance of the digital separation algorithm could be improved so that it can efficiently separate medium and long grains, the total processing time per 10-gram sample would be less than three minutes, or 30 minutes for a 100-gram sample. This would be much faster and more accurate than manual analysis which takes more than one hour.

### Repeatability of CVS Output

Based on comparison of results from analysis of 294 test samples (Table 7), the CVS gave a lower average coefficient of variation (CV) of 0.159 than manual method of analysis with an average of 0.363 for predicting 6 defective categories. This proves that the CVS has a better repeatability than manual method of analysis.

**Table 7.** Comparison of coefficient of variation between replicates of computer vision system (CVS) and Manual analysis

| Coefficient of Variation | CVS | Manual |
|---|---|---|
| Damaged | 0.131 | 0.504 |
| Sound | 0.007 | 0.266 |
| Chalky | 0.018 | 0.216 |
| Discolored | 0.215 | 0.236 |
| Immature | 0.127 | 0.492 |
| Red Kernels | 0.458 | 0.463 |
| **Average** | 0.159 | 0.363 |

*Samples processed: 294 batches*

## CONCLUSIONS

1. The flatbed scanner could be used as a low-cost alternative to digital cameras for computer vision systems. It is also simple to operate and does not require a separate controlled lighting system as in digital camera system.
2. The projected area of milled rice grains could be used to predict the weight of milled rice grain using a linear regression model.
3. The long axis of the grain area in combination with the weight prediction model could be used to predict the percentage by weight of head rice, broken rice, and brewers.
4. The artificial neural network using the generalized regression neural network (GRNN) predicted seven quality categories of sound, damaged, chalky, discolored, immature, red kernels, and palay using color features consisting of basic statistics from RGB and CIEL*a*b* color models.
5. The GRNN performed better when the chalky and immature categories were combined (R-square of 0.94) than when they are separate (R-square of 0.88 for chalky and 0.48 for immature).
6. The GRNN performed best when all the defective categories except paddy were combined together resulting to R-squares of 0.97 for sound, 0.97 for defectives, and 0.98 for palay.
7. The CVS has a better repeatability for predicting quality of milled rice than manual method.

## RECOMMENDATIONS

The following improvements for the developed CVS are recommended:

1. Improving the performance of the digital separation algorithm would result to a processing time of less than 3 minutes for a 10-gram sample and 30 minutes for a 100 gram sample. This would be faster than manual analysis which takes more than an hour.

2. Re-training the GRNN model by adding training samples to further improve the performance of the ANN. Additional features such as texture might also improve the classification capability of the GRNN model especially for damaged category.

3. Developing the model for milling degree and contrasting type of grain to complete the parameters for determining the rice grade as cited in the Philippine Grains Quality Standard.

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## ABOUT PHILMECH

The Philippine Center for Postharvest Development and Mechanization, known then as the National Postharvest Institute for Research and Extension (NAPHIRE), was created on May 24,1978 through Presidential Decree 1380 to spearhead the development of the country's postharvest industry.

As a subsidiary of the National Grains Authority in 1980, the agency's powers and functions were expanded in line with the conversion of NGA to the National Food Authority.

In 1986, PHilMech moved to its new home at the Central Luzon State University compound in Muñoz, Nueva Ecija.

The agency was transformed from a government corporation into a regular agency through Executive Order 494 in 1992. It was renamed the Bureau of Postharvest Research andExtension (BPRE).

For years now, PHilMech is engaged in both postharvest research, development and extension activities. It has so far developed, extended and commercialized its research and development outputs to various stakeholders in the industry.

With Republic Act 8435 or Agriculture and Fishery Modernization Act (AFMA) of 1997, PHilMech takes the lead in providing more postharvest interventions to empower the agriculture, fishery and livestock sectors.

Pursuant to Executive Order 366 or the government's rationalization program in November 2009, BPRE became the Philippine Center for Postharvest Development and Mechanization (PHilMech) with twin mandates of postharvest development and mechanization.

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