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Development of a Computer Vision System for Brown Rice Quality Analysis

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ABSTRACT--- ***Conventional brown rice analysis is done by visually inspecting each grain and classifying according to their respective categories. This method is subjective and tedious leading to errors in analysis. Computer vision could be used to analyze brown rice quality by developing models that correlate shape and color features with various classification. The objective of the study was to develop a computer vision system (CVS) for predicting quality parameters of brown rice.***

Brown rice training samples were collected in Nueva Vizcaya, NFA Binalonan, Pangasinan, and SM supermarket. An ordinary flat bed scanner was used as image acquisition device coupled to a laptop computer equipped with image processing and analysis software developed at PHilMech. The CVS set-up was tested using samples collected at the regional NFA warehouses. The performance of the CVS was compared to human inspection based on their capability to classify brown rice samples.

An artificial neural network using probabilistic neural network (PNN) model was developed. Sensitivity analysis revealed a true positive proportion ranging from 0.8792 to 1.00. Likewise, a weight prediction model based on the projected area was made using linear regression. The developed equation is y = 0.00148A – 0.00018 with a R^2 of 0.854.

The results of performance testing revealed that the CVS could predict the weight of brown rice and detect color-related quality of brown rice such as: sound, damaged, chalky/immature, yellow fermented, red, and paddy. Processing time for classification using the developed CVS has an average of 18.53 minutes and sixty percent of its time (equivalent to 11.24 minutes) was consumed in the manual arranging of grain samples. If a digital separation could be developed, the total time can be reduced to 7.11 minutes compared to 40.07 minutes of manual assessment. Moreover, CVS classification is more accurate compared with the human inspection.

Keywords--- brown rice, computer vision system, human inspection, accuracy, repeatability

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1. INTRODUCTION

Brown rice or pinawa in Tagalog was a popular staple among Filipinos until the early 1950s. Brown rice then was in the form of unpolished rice produced by hand pounding using mortar and pestle or stone grinder. With the introduction of milling machines that produce the white polished rice, consumer's tastes and preferences started to shift in favor of white rice.

PHilMech had developed a machine vision system for quality analysis of milled rice and yellow corn. The CVS for milled rice can predict six quality parameters with an R^2 of 0.94 for yellow, 0.93 for chalky, 0.91 for damage, 0.96 for paddy, 0.99 for red and 0.99 for sound. While the CVS for yellow corn can predict defectives such as damaged, immature, other color grains and foreign matter with an R^2 of 0.98.

With the effective enforcement Philippine Agricultural Engineering Standards (PAES) as part of the country's regulatory system, the Philippines will be protected from possible entry and sale of imported and locally produced postharvest facilities and equipment not conforming with the standards. Based on AMTEC test data bulletin for rice mills from 1998 – 2004, 60% of rice mills tested and evaluated are imported. Local manufacturers and distributors of rice mills are requesting AMTEC for testing and evaluation of their units to ensure that they are in accordance with PAES.

Brown rice analysis is the method prescribed by the PAES in assessing the technical performance of rice mills. Conventional brown rice analysis is done by visually inspecting each grain and classifying according to their respective categories. The manner of analysis is subjective, depends on the skill of the classifier, physical condition of the sample, and working conditions. It is also very tedious, costly and prone to errors.

Computer vision system (CVS) could be used to analyze brown rice quality by developing models that correlate shape and color features with various classification. 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" (Wang & Sun, 2001). Computer vision technology not only provides a high level of flexibility and repeatability at a relatively low cost, but also, and more importantly, it permits fairly high plant throughput without compromising accuracy. The food industry continues to be among the fastest-growing segments of machine vision application, and it ranks among the top ten industries that use machine vision systems (Gunasekaran, 1996).

The general objective of the study is to develop a computer vision system for predicting quality parameters of brown rice that make analysis of brown rice more objective and faster than existing methods..

2. MATERIALS AND METHODS

The freshly harvested, good quality and immature palay were collected in Nueva Vizcaya. Damaged palay and dried yellow fermented palay were gathered from the Alay Kapwa Cooperative and the warehouse of National Food Authority Binalonan, Pangasinan, respectively. However, the red rice was purchased at the SM supermarket. The collected good quality and immature samples were sundried prior to dehulling. The palay samples were dehulled using laboratory scale Satake dehuller of PHilMech following the Philippine Agricultural Engineering Standards (PAES) prescribed procedure.

The brown rice samples were classified by a trained classifier into sound, damaged, chalky, immature, paddy, red and yellow fermented which served as training samples. The classified samples were brought to Agricultural Machinery Testing and Evaluation Center (AMTEC) for verification.

Image Acquisition Set-up

A flat bed scanner (model HP scanjet G3110) was used as image acquisition device. A laptop computer equipped with image processing and analysis software was used in the processing and analysis of the images acquired.

Development of Algorithms for Image Processing of Brown Rice Images

Brown rice image processing algorithms ensure unnecessary information is filtered out from the image. The algorithms include a windows based graphical user interface for control of imaging hardware through a computer, image acquisition and storage, segmentation to filter out noise and background color from grain image, model to estimate weight of samples, measurement of grain size, and model to classify brown rice into sound, chalky, immature, damaged, paddy, red, and yellow fermented.

Extraction of Shape and Color Features

The developed PHilMech quality analysis software for brown rice was used to extract shape and color features of the brown rice grain image. Shape features such as area, perimeter, circularity, length, and width were extracted from each grain. Color features including basic statistics from the RGB and CIE L*a*b color components (e.g. statistical range, mean, standard deviation, and median) were extracted and summarized in Table 1.

Table 1. Color features extracted from each brown rice 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

Yun et al. (2002) used color algorithm to classify chalky rice, cracked rice, and milling rate in an image. Cyan (C), magenta (M), yellow (Y), and black (K) color intensity were calculated from the red, green, and blue color bands (RGB) of an image. Area, perimeter, and compactness size features isolate paddy and off-type rice grains.

Description of Color Features

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

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

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

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

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

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

Median is the pixel value with the highest number of occurrences.

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

Development of Model for Weight Prediction of Brown Rice

Weight measurements of around 1000 grain samples in each varying quality of different sizes, and shapes were taken and weighed using a 3-decimal digital balance (Metler model HR-120). The same grains were imaged individually and morphological features composed of area, roundness and perimeter were extracted from each grain image. Each morphological feature was correlated to weight using linear regression equation:

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

In the above equation, $K(A_i)$ is the weight of *i*th rice kernel in grams and A_i is the morphological feature of the *i*th blob and c_1 and c_2 are constants based on morphological features used.

Development of Model for Detection of Brown Rice Quality

A probabilistic neural network (PNN) was used to develop the model for detection of brown rice quality. An input consisting of 24 features extracted from brown rice images and six quality outputs, corresponding to sound, chalky/immature, damaged, paddy, red, and yellow fermented, were built using Neuroshell 2 (Ward Systems), an artificial neural network software. The dataset, consisting of about 26,968 grain images each of image acquisition device, was randomly arranged. The 75 percent was set aside for training, 20 percent for calibration, and the remaining 5 percent was set aside for testing the accuracy of the network classifier. Training was automatically stopped after 20 model generations with no improvement of 1 percent in the ANN model.

Luo, Jayas and Symons (1999) compared statistical versus neural network methods for classifying grains (CRWS wheat, CWAD wheat, barley, oats, and rye). Classification accuracies using a parametric classifier with quadratic discriminant functions were lower than k-nearest neighbor and multilayer neural network (MNN) with back propagation learning algorithm classifiers. MNN was recommended for practical implementation in the grain industry. For a k-nearest neighbor, all the training data set must be retained to keep the class probability information. This means a large amount of computer memory is needed and the classification process is slow especially when a large training set is used.

Performance Evaluation of Brown Rice CVS

The performance of the CVS set-up was compared with manually analyzed samples to evaluate its accuracy, repeatability, and speed. The parameters used for comparison consisted of weight prediction, prediction of color-related quality and speed. Actual weight was obtained using a 3-decimal digital balance (Metler model HR-120). All samples were scanned three times in a non-touching fashion. Variance was computed among 10 replicates of the CVS and manual method to compare their repeatability. Number of samples processed per time interval was recorded to evaluate the speed of analysis.

Statistical Analysis

The data gathered in the accuracy test and weight measurement were analyzed using completely randomized design (CRD). ANOVA table was utilized to determine the level of significant among treatments. The difference among means was analyzed using Scheffe test.

3. RESULTS AND DISCUSSION

Description of Image Acquisition Device

Figure 1 shows the HP scanjet (G3110) flat bed scanner with a charged-coupled device (CCD) scanning element coupled to a laptop computer. A black acrylic plastic was placed on the bottom cover of the scanner to serve as the background. Around 580 brown rice kernels were spread manually in a single layer using a customized template made of acrylic plastic in the glass surface of the scanner to avoid grains touching each other. A 7 x 9 inches image of the grain at 200 dots per inch (dpi) resolution was acquired and saved as uncompressed bitmap file. Moreover, the scanner automatic exposure and color settings were disabled to ensure consistent readings.

Figure 1. An HP scanjet (G3110) flat bed scanner coupled with a laptop computer

The image acquisition device was complimented by a laptop (Intel Core i3, 2.0 GHz, 2 GB RAM, 320 GB HDD) computer. The interface connection for the scanner and the camera to the computer was made using universal serial bus (USB 2.0) port.

Image Processing Software

Figure 2 shows the developed PHilMech developed Grain Quality Evaluation Software for brown rice. The executable file of the software was around 16MB. It has the capability to recognize the yellow fermented, chalky, damage, paddy, red and sound kernel and to estimate the weight of the grains.

Figure 2. Main menu of quality evaluation software for brown rice

Brown Rice Quality Classification Colors and Signatures

Grain color

Figures 3 and 4 show the colors of brown rice and milled rice and its defects. It was observed that the colors of defective grains of brown rice are different after milling operation especially in sound, yellow fermented, chalky/ immature and red.

Figure 3. Color of brown rice and its defectives after hulling operation

Figure 4. Color of milled rice and its defectives after milling operation

Histogram of brown rice

Twenty four color features were extracted from each grain image to correlate with the brown rice classification. Figure 6 shows the histogram of brown rice sample. The gray-scale histogram of an image represents the distribution of the pixels in the image over the gray-level scale.

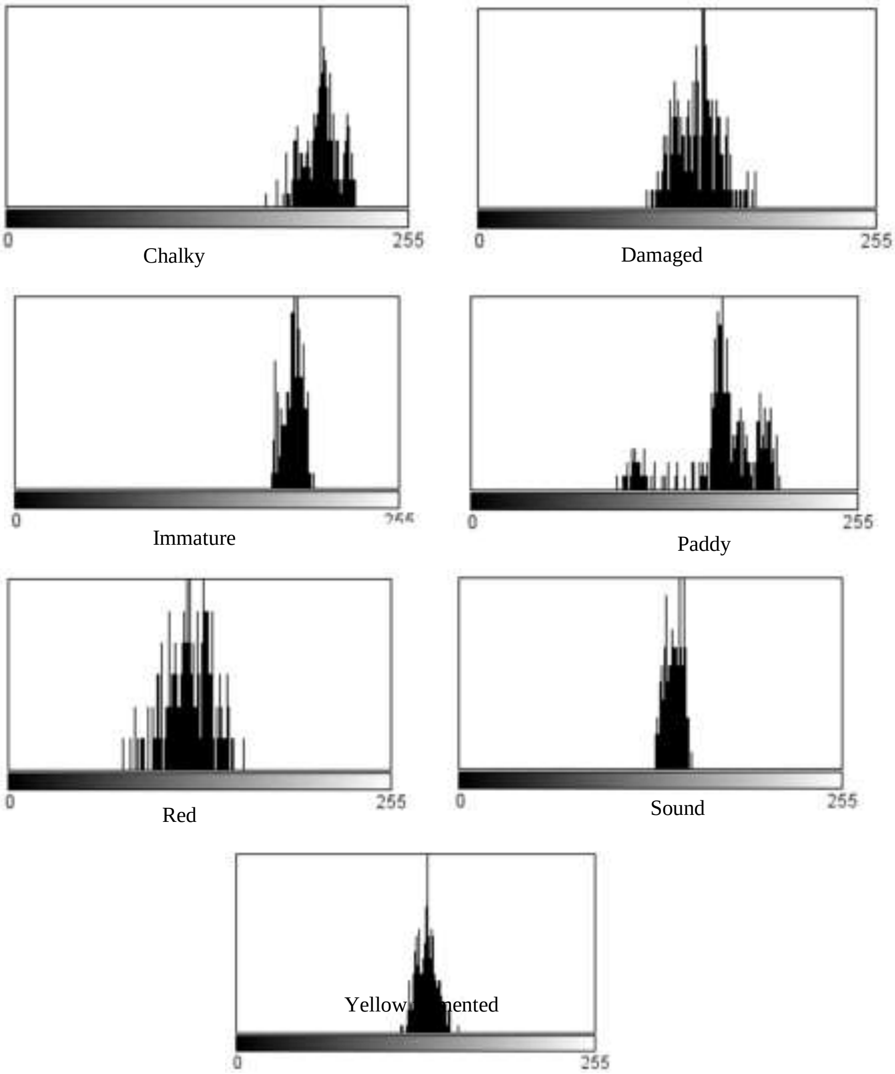

Figure 6. Histogram of brown rice sample

Statistical Pattern Recognition and Classification Model

Neural Network Model

Probabilistic Neural Network (PNN), is another neural network architecture used for classifying agricultural products. Statistically paralleled by kernel discriminant analysis, probabilistic neural networks are based on the Bayesian strategy for pattern recognition, which postulates that a decision rule to classify patterns should minimize “expected risk” of misclassification. Training patterns determine the window positions and responses so that new inputs will generate a response that is similar to the response generated by the training data that they resemble (Hush and Horne, 1993). Steenhoek et al. (2001a) stated that, as with other pattern recognition techniques, PNNs require that training data be available from the entire solution space domain. A PNN can be trained with sparse data but cannot interpolate between missing classification patterns. PNNs are feed forward neural networks and respond to an input pattern by processing the input data from one layer to the next with no feedback paths. An inherent advantage of the PNN architecture is that it can be made to respond only to inputs that are in the same region of the training data input space. Inputs outside the learning area can be flagged, thus avoiding extrapolation errors. Furthermore, training the network to have a proper response in a part of measurement space does not disturb the trained response in other distant parts of the measurement space. Other advantages include: PNNs train quickly as only one pass through the data is required, PNNs have only one free parameter, the smoothing factor, to be adjusted by the user and this factor can be adjusted at run time without the requirement of network retraining, Shape of the decision surface can be made as complex as necessary. It can also be made very simple by choosing appropriate values for the smoothing factor, Sparse samples are adequate for network performance, Results are not dependent on randomization order of training data and Training can be incremental as data becomes available and old patterns can be "forgotten" and replaced by new patterns if so desired.

A Neural Network Architecture Model was employed to model the classification of brown rice into the defined classes as shown in Figure 6. The architecture comprised a 24-node inputs, 1 hidden layer of 26,968 nodes, and an output layer with a single node.

Artificial neural network analysis was used in both the training and validation datasets to establish the classification models.

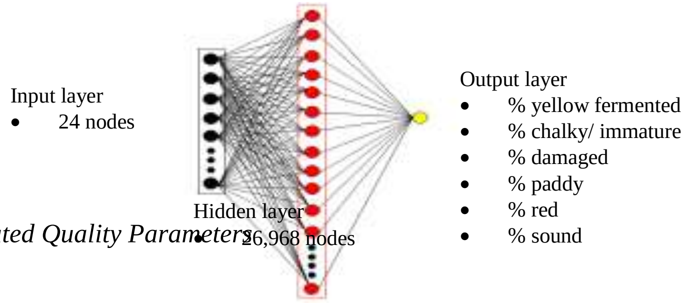

Figure 6. A probabilistic neural network architecture

Color-related Quality Parameters

Table 2 shows the sensitivity analysis of probabilistic neural network (PNN) of Neuroshell 2 applied to the combined data set for predicting six color-related quality parameters from test samples. The sensitivity analysis indicated that proportion of the brown rice classifications that the PNN correctly diagnosed was 0.9545 (84/88 yellow), 0.9468 (498/526 chalky/ immature), 0.8792 (211/240 damaged), 0.9630 (78/81 paddy), 1.0 (181/181 red), and 0.9868 (225/228 sound). However, it was observed that damaged category had the lower true positive proportion, this could be associated with the broad characteristics of damaged grains due to insects, water stress, and diseases resulting to a wide and varied color pattern.

Table 2. Sensitivity analysis of probabilistic neural network (PNN)

Categories	Yellow Fermented	Chalky/ Immature	Damaged	Paddy	Red	Sound
Actual winners	88	526	240	81	181	228
Classified winners	95	506	221	86	182	254
Actual losers	1256	818	1104	1263	1163	1116
Classified losers	1249	838	1123	1258	1162	1090
True positives	84	498	211	78	181	225
False positives	11	8	10	8	1	29
True negatives	1245	810	1094	1255	1162	1087
False negatives	4	28	29	3	0	3
True positives proportion	0.9545	0.9468	0.8792	0.9630	1.000	0.9868
False positives proportion	0.0088	0.0098	0.0091	0.0063	.0009	0.0260

The following define the terminology for categories: Actual winners: The number of times this output was set to 1 in the file. Classified winners: The number of times the network sets this output to 1. Actual losers: The number of times this output was set to 0 in the file. Classified losers: The number of times the network sets this output to 0. True positives: The number of times an actual value of 1 in the file was classified a 1 by the network. False positives: The number of times an actual value of 0 was classified a 1 by the network. True negatives: The number of times an actual value of 0 was classified a 0 by the network. False negatives: The number of times an actual value of 1 was classified a 0 by the network. True positive proportion: The ratio of true positives to actual winners. False positive proportion: The ratio of false positives to actual losers.

Weight Prediction Model

A weight prediction model based on the projected area, perimeter and circularity of a brown rice kernel were made using linear regression. Figure 7, 8, and 9 show the linear regression equation of the projected area, perimeter and circularity of the brown rice grain versus its actual weight. The computed R^2 for area, perimeter and circularity were 0.854, 0.836 and 0.519, respectively. The results were in agreement with the works of Bulaong et. al, and Paliwal et al that the extracted projected area of milled rice, barley, wheat, oats and rye grains gave the highest correlation to the weight of the grain.

The linear equation for the weight prediction model using projected area was:

$$Y = 0.00148A – 0.00018$$

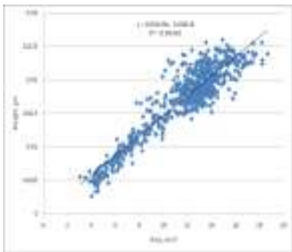

Figure 7. The linear regression of the projected area of the grain versus its actual weight

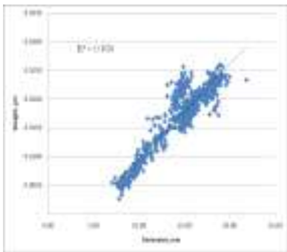

Figure 8. The linear regression of the projected perimeter of the grain versus its actual weight

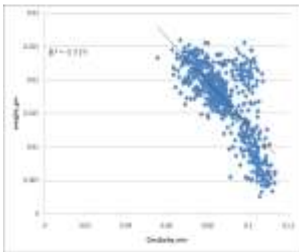

Figure 9. The linear regression of the projected circularity of the grain versus its actual weight

Performance Evaluation of Brown Rice CVS

The performance of the CVS was tested and evaluated using brown rice samples collected in the NFA warehouses to further validate its performance. The CVS was evaluated by comparing its speed, accuracy and repeatability with manual method.

Speed

Table 3 presents the processing time consumed in the classification of brown rice samples using computer vision system set-up and manual method. The lowest processing time of 18.53 minutes per 25 gram sample was obtained in the computer vision set-up. This could be attributed to the short time consumed in the processing and analysis using the developed PHilMech quality evaluation software. It was also observed that the arranging of grain samples consumed an average of 11.24 minutes or almost 60 percent of the total processing time.

On the other hand, manual method consumed longer time in classifying brown rice samples which was about 40.07 minutes per 25 gram sample. This was due to the similarity in the color of the brown rice and the classifier could not distinguish easily the samples especially the yellow fermented, sound, chalky/ immature grains.

Table 3. Processing time consumed in the classification sample

Mode of Classification	Replicate			Mean
	R1	R2	R3	
CVS	20.06	17.87	17.62	18.53a
Manual	38.02	38.38	43.80	40.07b

Means side scored by the same letter(s) are not significantly different at 5% level using scheffe.

The analysis of variance revealed significant differences on the time consumed in the classification of 25 gram sample using computer vision system and manual method.

Weight

Table 4 shows the actual mean weight of brown rice samples and its predicted weight value generated using the developed brown rice CVS. The means of predicted weight of brown rice samples were higher compared to its actual weight. However, there are no significance difference on the weight of brown rice samples on the mode of classifications and source of samples.

Table 4. The actual mean weight of brown rice samples and its predicted weight value, gm

Mode of Classification	Source (Region)							Mean
	I	II	IV	VII	XI	XIII	XIV	
CVS	23.30	25.07	25.23	24.79	24.96	24.47	25.09	24.70
Actual weight	22.88	24.87	25.02	24.27	24.75	24.18	24.99	24.42
Mean	23.09	24.97	25.12	24.53	24.85	24.32	24.04	24.56

Means side scored by the same letter(s) are not significantly different at 5% level using scheffe.

Repeatability

Table 6 shows the computed variance of the CVS and manual method in classifying brown rice. The variance was used to determine the consistency of both method to classify the quality parameters of brown rice samples. The computed average variances of the CVS and manual method were 0.020 and 0.016, respectively. Moreover, the computed variances of damaged and chalky/ immature grains on the CVS was higher compared to manual method, this could be associated with the broad characteristics of damaged grains and the exposure of color white of chalky grain in the scanning element of image acquisition device.

Table 6. The computed variances of the two mode of classifications of brown rice sample

Classifications	CVS	Manual
Yellow fermented	0.004	0.025
Chalky/ Immature	0.017	0.009
Damaged	0.035	0.002
Red	0.000	0.000
Sound	0.045	0.048
Average	0.020	0.016

Accuracy test

The accuracy of the computer vision system was a measure of the efficiency of the set-up to classify the brown rice samples according to their respective classifications.

Figures 10 and 11 show the performance of the CVS and human inspection on an 8-hour period. The performance of CVS is more accurate compared with the human inspection. However, the inconsistency of manual inspection in particular with yellow fermented, chalky and damaged kernels can be attributed to tiredness and eyes stress of the classifier during classification.

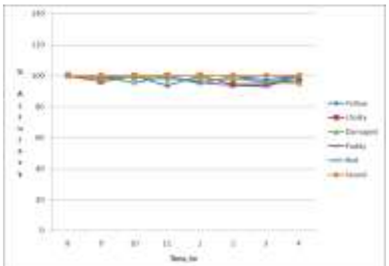

Figure 10. Performance of CVS over an 8-hour period

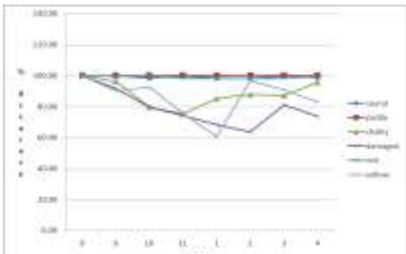

Figure 11. Performance of manual inspection over an 8-hour period

4. CONCLUSIONS

The developed CVS for brown rice will automate manual method in assessing the milling quality of brown rice and reduce the tedious and subjective manual method of evaluation.

The artificial neural network using PNN predicted the six quality categories of brown rice: sound, chalky/ immature, damaged, red, paddy and yellow fermented.

The processing time of CVS for classifying brown rice samples is shorter by around 22 minutes to manual assessment. This could be further improved if a digital separation algorithm could be developed. Moreover, CVS classification is more accurate compared with human inspection.

5. ACKNOWLEDGEMENT

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