

Classifying Paddy Rice by Morphological and Color Features Using Machine Vision

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ABSTRACT

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From five paddy rice cultivars grown in Taiwan and harvested in the summers of 1997, 1998, and 1999, five calibrated models were established by backpropagation neural network program through different morphological and color features selection for classifying paddy rice harvested in the summer of 2000. With 60 features, the average classification rates of Model 1 and Model 5 were 92 and 99.8%, respectively. With the most effective 50 features, by loading in the first principal component, the average classification rate of Model 2 was 90.0%. With 35 features selected from the correlation coefficient matrix, the average classification rate of

Model 3 was 91.0%. With the most effective 20 features of area, area/perimeter, 48th width, shape factor, maximum length/maximum width, average intensity of blue, maximum length, average intensity of green, 47th width, 50th width, average intensity of red, 1st width, 19th width, 5th width, 6th width, 29th width, perimeter, 46th width, 42nd width, and 4th width based on the contribution of the training model, the average classification rate of Model 4 was 91.8% and would be recommended for classifying five paddy rice cultivars of set trading prices because it required fewer features and held a stable classification rate.

The traditional method for classifying cultivars of paddy rice relies mostly on physical morphological observation, which requires experts to judge cultivars using charts and illustrations of kernel characteristics. For example, to classify the different cultivars of paddy rice, the outer characteristics are observed by the ratio of length to perimeter of the kernel, the existence of beards and the length of beards, the color of the hull, the color of the inner and outer awn, the floss growth situation, etc. Except for these specific features, it is difficult to categorize the cultivars that have a similar outer appearance using only physical observation, which is prone to human error and is also time-consuming. In addition, considerable time is required to train such experts. Using machine vision, Zayas et al (1986) classified 77–83% of hard red winter and soft red winter wheat. Barker et al (1992) showed that aspect ratios provided 60–63% correct classification for eight wheat cultivars, compared with 52–55% for slices. Shatadal et al (1995) classified and separated kernels of hard red spring wheat, durum wheat, barley, oats, and rye with 95% correct kernel classification. Luo et al (1999) reported on the classification of cereal grains using the *k*-nearest neighbor statistical classifier or multi-player neural network classifier with classification rates of 96.9–99%. Wang et al (1999) applied principal component analysis to reduce the number of neural network inputs and achieved 98% classification accuracy for six classes of wheat. Burks et al (2000) applied the best symmetrical backpropagation neural network for classifying weed species and achieved 94.7% accuracy. Majumdar and Jayas (2000) classified Canada Western Red Spring wheat, Canada Western Amber Durum wheat, barley, oats, and rye with 99.7–99.8% accuracy using the morphology-texture-color model. Chang et al (2000) validated six classes of paddy rice with a 95.8% validation rate: Tainung Sen 20, Tainung 67, Tainung 70, Taichung Sen 10, Taikeng 8, and Taikeng 9 grown at the Taichung District Agricultural Improvement Station in the summers of 1997 and 1998. Classifying paddy rice cultivars based on the serial differences of deoxyribonucleic acid (DNA) is very precise but very expensive and not suitable for calculating pricing for paddy rice for market in Taiwan.

Tsang et al (1990) selected 11 from 74 characteristics to build a discrimination model, combining an average of more than eight observations, and produced results that showed an average discrimination rate >89.5% among three rice cultivars (Tainung 70, Tainung 67, and Hsingchu 64) excluding four cultivars (Tainung Sen 20, Taichung 10, Taikeng 8, and Taikeng 9). Paliwal et al (2001, 2003) showed that the artificial neural network was suitable for machine vision classification of barley, wheat, oats, and rye, excluding paddy rice. Using five paddy rice cultivars (Tainung Sen 20, Taichung Sen 10, Tainung 67, Taikeng 8, and Taikeng 9) grown in central, eastern, and southern Taiwan and harvested in the summers of 1997, 1998, and 1999, five calibrated models with yearly adjustments were established using four different features. The models were used to classify paddy rice grown in the same areas and harvested in the summer of 2000. The best model would be recommended for classifying paddy rice cultivars in order to set trading prices.

MATERIALS AND METHODS

As shown in Fig. 1, five paddy rice cultivars including Tainung Sen 20, Taichung Sen 10, Tainung 67, Taikeng 8, and Taikeng 9 were grown in central, eastern, and southern Taiwan and harvested in the summers of 1997, 1998, 1999, and 2000. Before the test, these samples were packed in mesh bags, stored at 5°C, and then conditioned to ≈13% moisture content in a controlled temperature and humidity chamber at 25°C and 70% rh for four days.

A charge couple device (Watec CCD) camera or an NTSC compound colored visual signal (U.S. National Television Standards Committee) with a resolution of NTSC-512 × 512 pixels was used as an RGB signal output device. An image acquisition card (PXC200) with a resolution of NTSC-640 × 480 pixels was used to take the sample images in a darkroom. Image processing software was programmed by Borland C++ to analyze each paddy rice kernel for 60 characteristic features. The measured features included the maximum length, the maximum width, the ratio of maximum length to maximum width, the area, the perimeter, the ratio of the area to the perimeter, and the shape factor [$4\pi \times (\text{the area})/(\text{the perimeter})^2$] (Travis and Draper 1985). Each kernel's average color intensities of red (R), green (G), and blue (B) were measured. The value for 1/50 of the width of the kernel on the length axis is described in Fig. 2. Because Tsang et al (1990) built a calibrated model combining an average of 10 samples, we used 806 average samples from 1997, 1998, and 1999 for training sets and 425 average samples for validation sets. A total of 500 samples, harvested in 2000, were used for classification. Software for NeuralWorks Professional II /PLUS (Neural Ware, Carnegie, PA)

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was used for training, validating, and classifying samples using the backpropagation neural network program. MATLAB 6.5 high-performance numerical computation software issued by MathWorks (Natick, MA) was used for analyzing the statistical results.

Model 1 had 60 features including area, perimeter, shape factor, the ratio of area to perimeter, the maximum width, the maximum length, the ratio of maximum length to maximum width, the average intensities of red, green, and blue, and the value of the widths, along the length. The features were separated into 50 divisions for each paddy rice kernel and input into a backpropagation neural network for training to find a calibrated model.

After principal component (PC) processing, each feature had a loading between -1 and $+1$ on each PC. It reflected both how much the feature contributed to that PC and how well that PC took into account the variation of that feature over the data points (Unscrambler, CAMO ASA, Oslo, Norway). Then the absolute value for each loading of each feature was rearranged for each feature by loading from high to low. By loading in the first PC, Model 2 selected the 50 most effective features, which were put into a backpropagation neural training network to find a calibrated model. The 50 most effective features (in order) were area, 4th width, 5th width, 6th width, 7th width, 8th width, 3rd width, 9th width, perimeter, 10th width, 11th width, 12th width, 13th width, area/perimeter, 14th width, 15th width, 2nd width, average intensity of blue, 1st width, 16th width, 17th width, 18th width, maximum length, 39th width, 19th width, 38th width, 40th width, 37th width, 36th width, 20th width, 41st width, 35th width, 21st width, 34th width, 22nd width, 42nd width, 33rd width, maximum width, 23rd width, 32nd width, 31st width, 24th width, 25th width, 23rd width, 26th width, 30th width, 26th width, 29th width, 27th width, and 28th width.

From Shen (2003), the two-dimensional correlation coefficient matrix of each feature ($m \times n$ matrix, where m and n are sample size and number of features, respectively) was found. Taking the absolute value of each element and calculating the average of each column, this reduced the two-dimensional correlation coefficient matrix to a one-dimensional correlation coefficient vector and rearranged each feature by correlation coefficient from low to high. The 35 features selected from the correlation coefficient matrix for Model 3 were shape factor, maximum length/maximum width, 50th width, area, 1st width, 49th width, 2nd width, 48th width, area/perimeter, 47th width, 3rd width, 4th width, 46th

width, 5th width, 45th width, 6th width, 7th width, 44th width, 8th width, 43rd width, 9th width, 42nd width, 10th width, 41st width, 11th width, 12th width, 40th width, 13th width, average intensity of blue, 39th width, 14th width, 15th width, 16th width, 38th width, and 17th width, according to the correlation coefficient matrix from low to high.

After completing model training using 60 features by Neural-Works Professional II/PLUS, the neural network offered the contribution of each feature, pointed out which feature was more effective on the model, and then rearranged each feature by contribution from high to low. Based on the contribution, the most effective 20 features were selected for Model 4 from the 60 features listed in Model 1. In the order of the largest to the smallest contribution, these features were area, area/perimeter, 48th width, shape factor, maximum length/maximum width, average intensity of blue, maximum length, average intensity of green, 47th width, 50th width, average intensity of red, 1st width, 19th width, 5th width, 6th width, 29th width, perimeter, 46th width, 42nd width, and 4th width.

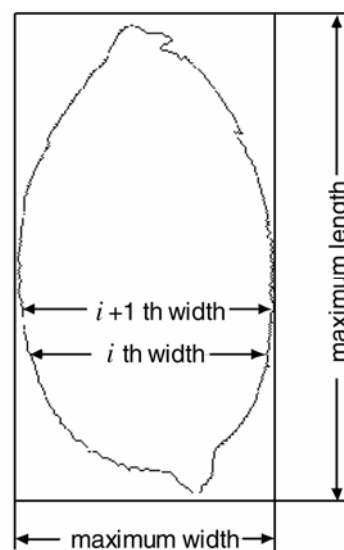


Fig. 2. Definition of width and length of paddy rice (i from 1–49).

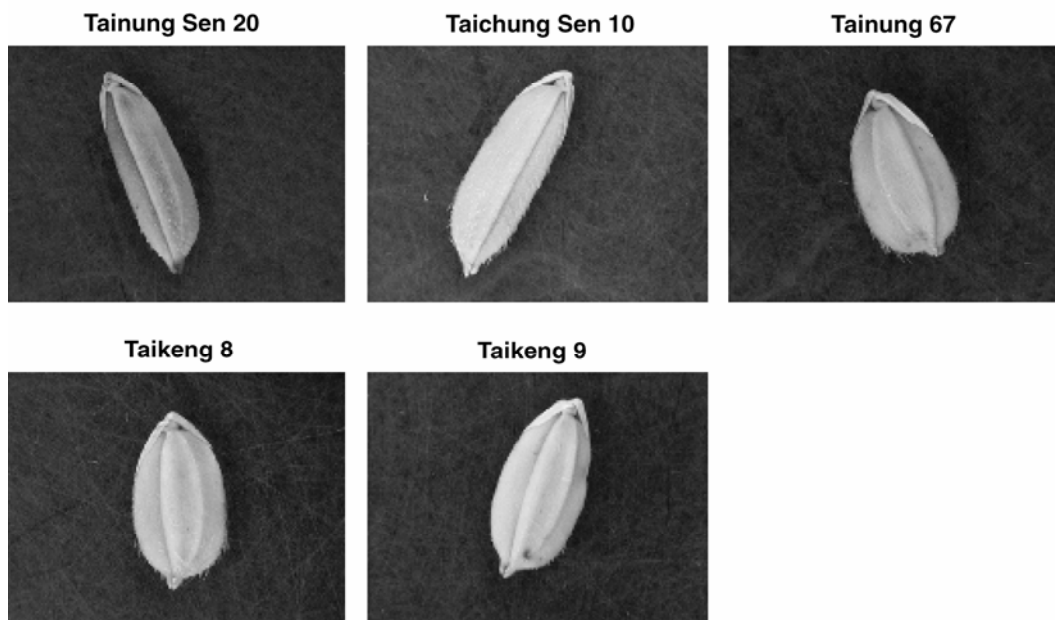


Fig. 1. Images of five paddy rice cultivars.

By treating Tainung 67 and Taikeng 8 as the same cultivar, the 60 features listed in Model 1 were input into the neural network to produce Model 5.

RESULTS AND DISCUSSION

As shown in Table I, Model 1, with 60 features, two hidden layers with 40 nodes in the first hidden layer, and 35 nodes in the second hidden layer, 50,000 epochs, 0.4 momentum, root mean square (RMS) error equal to 0.1, and a correlation coefficient equal to 0.93 had an average validation rate in 1997, 1998, and 1999 of 92.2% with 4.8% standard deviation. The highest validation rate of Tainung Sen 20 was 97.7%, in which only two of 85 samples were not validated. The poorest validation rate of Tainung 67 was 85.9%, in which only 73 out of the 85 samples were validated. Of the total 425 samples, 33 were not properly validated, 18 of which (54.6%) included Tainung 67 and Taikeng 8. As Model 1 was established, the average classification rate for five paddy rice cultivars harvested in the summer of 2000 was 92% with 11.0% standard deviation (Table I). Twenty-one samples of Tainung 67 were misclassified as Taikeng 8 and 19 samples of Taikeng 8 were misclassified as Tainung 67. From this result, it may be assumed that Tainung 67 and Taikeng 8 have close physical morphological shapes (Fig. 1).

Forty fixed nodes in the first hidden layer, and nodes in the second hidden layer changing from 10, 15, 20, 25, 30, 35, and 40, had the highest average validation rate for Model 1 at 92.2%. For 35 nodes, the lowest average validation rate was 90.4% with 10 nodes. There were no significant differences, however, in the average validation rate for the five paddy rice cultivars. Similarly, the highest average classification rate for Model 1 was 92% with 35 nodes.

By selecting the most effective 50 features from the loading in the PC1 axis, with 40 nodes in the first hidden layer and 25 nodes in the second hidden layer, 50,000 epochs, 0.4 momentum, RMS error equal to 0.1, and with a correlation coefficient equal to 0.89, Table II shows that the average validation rate of Model 2 was 91.8% with 5.3% standard deviation. By changing the loading features from 10 to 55, the average validation rates for Model 2 were 73.4–91.8%. For classifying the paddy rice cultivars harvested in

the summer of 2000, the average classification rate for Model 2 (Table II) was 90.0% with 19.7% standard deviation. By changing the loading features from 10 to 55, the average classification rates of Model 2 were 64.0–90.6%.

By selecting 35 features from the correlation coefficient matrix for Model 3, with 25 nodes in the first hidden layer and 10 nodes in the second hidden layer, 50,000 epochs, 0.4 momentum, RMS error equal to 0.09, and with a correlation coefficient equal to 0.94, the average validation rate for the samples in 1997, 1998, and 1999 was 89.88% with 6.31% standard deviation, as shown in Table III. By changing the features from 10 to 35, the average validation rate varied from 76.2% to 89.9%. By increasing the features from 35 to 55, the average validation rate was not improved further. For classifying the cultivars of paddy rice harvested in the summer of 2000, the average classification rate of Model 3 was 91.0% with 13.4% standard deviation. By changing the features from 10 to 55, the average classification rate for Model 3 were 57.8–91.4% (Table III).

Selecting the 20 most effective features from the contribution of the training model, with 20 nodes in the first hidden layer and 15 nodes in the second hidden layer, 50,000 epochs, 0.4 momentum, RMS error equal to 0.08, and with a correlation coefficient equal to 0.85, the average validation rate for Model 4 was 90.6% with 6.1% standard deviation, as shown in Table IV. By increasing the features from 25 to 55, the average validation rate for Model 4 was 89.4–92.9%.

For classifying the paddy rice cultivars harvested in the summer of 2000, the average classification rate for Model 4 was 91.8% with 15.7% standard deviation. By increasing the features from 25 to 55, the average classification rate for Model 4 was 89.6–91.0% (Table IV).

By treating Tainung 67 and Taiken 8 as the same cultivar, Model 5 with 60 features, 40 nodes in the first hidden layer and 20 nodes in the second hidden layer, with 50,000 epochs, 0.4 momentum, RMS error equal to 0.07, and with a correlation coefficient equal to 0.97, the validation rates of Tainung Sen 20, Taichung Sen 10, Tainung 67 plus Taikeng 8, and Taikeng 9 were 98.8, 95.3, 98.2, and 85.9%, respectively. For classifying the paddy rice cultivars harvested in the summer of 2000, the classification rates were 100, 100, 100, and 99%, respectively.

TABLE I
Validation (Val) and Classification (Cla) Rates (% with SD) and Samples Distribution of Model 1

	Tainung Sen 20		Taichung Sen 10		Tainung 67		Taikeng 8		Taikeng 9	
	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla
Tainung Sen 20	83 (97.7%)	100 (100%)	2 (2.4%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Taichung Sen 10	3 (3.5%)	0 (0%)	82 (96.5%)	100 (100%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Tainung 67	0 (0%)	0 (0%)	0 (0%)	0 (0%)	73 (85.9%)	79 (79%)	12 (14.12%)	21 (21%)	0 (0%)	0 (0%)
Taikeng 8	0 (0%)	0 (0%)	1 (1.2%)	0 (0%)	6 (7.1%)	19 (19%)	77 (90.6%)	81 (81%)	1 (1.18%)	0 (0%)
Taikeng 9	0 (0%)	0 (0%)	0 (0%)	0 (0%)	6 (7.1%)	0 (0%)	2 (2.4%)	0 (0%)	77 (90.6%)	100 (100%)

^a Average validation and classification rates were 92.2% with 4.8% standard deviation and 92.0% with 11.0% standard deviation, respectively.

TABLE II
Validation (Val) and Classification (Cla) Rates (% with SD) Varied as Loading Values Changed on the First Principal Component Axis (Model 2)

Features	Tainung Sen 20		Taichung Sen 10		Tainung 67		Taikeng 8		Taikeng 9		Average		SD	
	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla
10	88.2	100	95.3	100	61.2	20	64.7	92	57.7	8.0	73.4	64.0	17.1	46.0
15	92.9	100	94.1	100	63.5	19	64.7	100	58.8	8.0	74.8	65.4	17.2	47.5
20	95.3	100	92.9	100	78.8	29	64.7	100	57.7	1.0	77.9	66.0	16.7	47.6
25	95.3	100	95.3	100	89.4	34	81.2	100	80.0	100	88.2	86.8	7.4	29.5
30	97.7	100	91.8	100	87.1	33	84.7	100	84.7	100	89.2	86.6	5.5	30.0
35	98.8	100	92.9	100	78.8	25	88.2	100	83.5	100	88.5	85.0	7.8	33.5
40	97.7	100	94.1	100	89.4	45	87.1	99	85.9	100	90.8	88.8	5.0	24.5
45	97.7	100	94.1	100	81.2	30	87.1	100	89.4	100	89.9	86.0	6.4	31.3
50	98.8	100	95.3	100	90.6	55	85.9	95	88.2	100	91.8	90.0	5.3	19.7
55	97.7	100	95.3	100	87.1	63	85.9	90	89.4	100	91.1	90.6	5.2	16.0

TABLE III
Validation (Val) and Classification (Cla) Rates (%) Varied as the Number of Features Changed by Correlation (Model 3)

Features	Tainung Sen 20		Taichung Sen 10		Tainung 67		Taikeng 8		Taikeng 9		Average		SD	
	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla
10	97.7	100	96.5	100	75.3	41	48.3	2	63.5	46	76.2	57.8	21.3	42.1
15	96.5	100	95.3	100	71.8	46	81.2	97	67.1	98	82.3	88.2	13.4	23.6
20	97.7	100	96.5	100	82.4	46	82.4	97	71.8	98	86.2	88.2	10.9	23.6
25	96.5	100	96.5	100	83.5	47	80.0	95	72.9	99	85.9	88.2	10.4	23.1
30	96.5	100	95.3	100	85.9	67	83.5	90	84.7	100	89.2	91.4	6.2	14.3
35	97.7	100	95.3	100	83.5	85	88.2	70	84.7	100	89.9	91.0	6.3	13.4
40	96.5	100	96.5	100	87.1	79	82.4	73	84.7	100	89.4	90.4	6.7	13.3
45	96.6	100	95.3	100	82.4	69	87.1	83	92.9	100	90.8	90.4	6.0	14.1
50	97.7	100	96.5	100	89.4	73	83.5	79	89.4	100	91.3	90.4	5.8	13.3
55	97.7	100	95.3	100	87.1	72	84.7	82	89.4	100	90.8	90.8	5.5	13.1

TABLE IV
Validation (Val) and Classification (Cla) Rates (%) Varied as the Number of Most Effective Features Changed (Model 4)

Features	Tainung Sen 20		Taichung Sen 10		Tainung 67		Taikeng 8		Taikeng 9		Average		SD	
	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla	Val	Cla
10	97.6	100	95.3	100	78.8	42	78.8	93	72.9	100	84.7	87.0	11.0	25.3
15	97.7	100	97.7	100	81.2	43	84.7	98	76.5	100	87.5	88.2	9.7	25.3
20	97.7	100	96.5	100	88.2	64	84.7	95	85.9	100	90.6	91.8	6.1	15.7
25	98.8	100	96.5	100	88.2	63	81.2	92	82.4	100	89.4	91.0	8.0	16.0
30	97.75	100	97.7	100	88.2	80	85.9	69	88.2	100	91.5	89.8	5.7	14.5
35	100.0	100	96.5	100	82.4	71	90.6	80	90.6	100	92.0	90.2	6.7	13.8
40	98.8	100	97.7	100	92.9	76	83.5	76	90.6	100	92.7	90.4	6.1	13.2
45	98.8	100	96.5	100	88.2	77	83.5	71	90.6	100	91.5	89.6	6.2	14.4
50	98.8	100	96.5	100	98.8	88	80.0	60	90.6	100	92.9	89.7	8.0	17.3
55	97.7	100	97.7	100	85.9	75	84.7	77	91.8	100	91.5	90.4	6.2	13.2

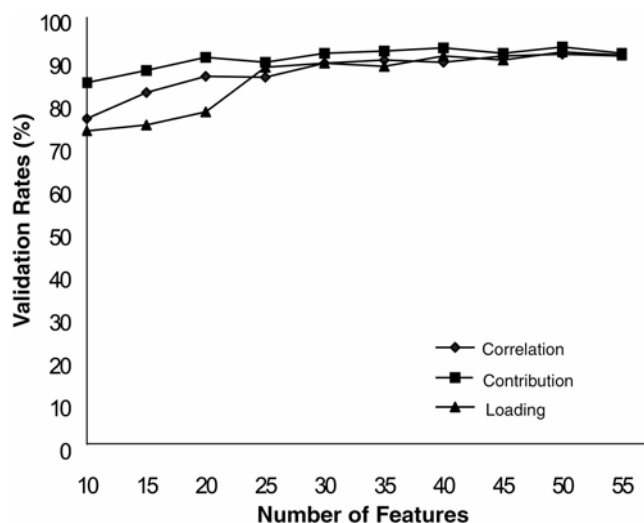


Fig. 3. Validation rates were changed as features were chosen from the correlation (Model 3), contribution (Model 4), and loading (Model 2).

As shown in Fig. 3, the validation rates for Model 2, Model 3, and Model 4 were not significantly different with more than 30 features. With 25 features or less, the validation rates for Model 2 and Model 4 decreased significantly. However, Model 3 had relatively stable validation rates when changing from 10 to 55 features. If 20 features were chosen, Model 4 offered a better validation rate than did Models 2 and 3.

As shown in Fig. 4, the classification rates for Model 2, Model 3, and Model 4 were not significantly different, with more than 25 features. For less than 25 features, the classification rates for Model 2 decreased significantly. Model 3 and Model 4 held relatively stable classification rates when changing from 10 to 55 features. If 20 features were chosen, Model 4 offered a better classification rate than did Models 2 or 3.

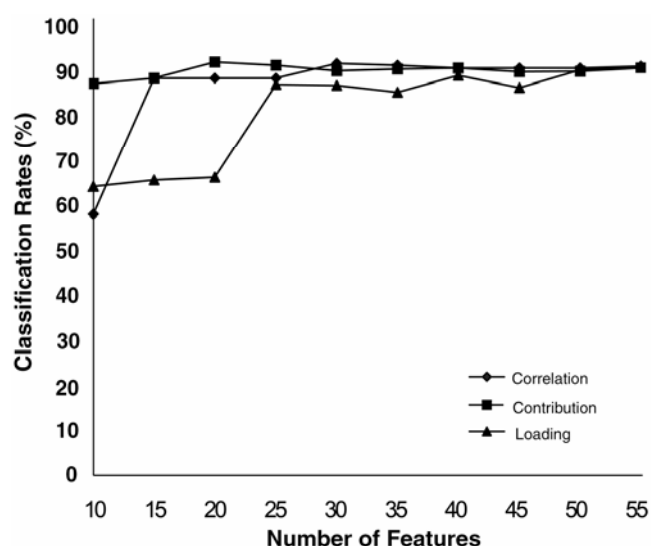


Fig. 4. Classification rates were changed as features were chosen from the correlation (Model 3), contribution (Model 4), and loading (Model 2)

Morphological and color features using machine vision and a backpropagation neural network with supervised learning was a very effective method for classifying paddy rice cultivars. By loading in PC1, by correlation coefficient matrix, and based on the contribution of the neural network training, the result may reduce feature numbers, save time, and improve classification rates. A similar method has been applied for classifying weed species, Canada Western Red Spring wheat, Canada Western Amber Durum wheat, barley, oats, and rye (Burks et al 2000; Majumdar and Jayas 2000; Paliwal et al 2001, 2003). Combining the contribution of the neural network training and backpropagation neural network, Model 4 with only 20 features may be the best and would be recommended to the Taiwan grain industry for classifying current cultivars of paddy rice in order to set trading prices.

CONCLUSIONS

From five cultivars of paddy rice (Tainung Sen 20, Taichung 10, Tainung 67, Taikeng 8, and Taikeng 9) grown in central, eastern, and southern Taiwan and harvested in the summers of 1997, 1998, and 1999, five calibrated three-year models were established and used to classify paddy rice that had been grown in the same areas and harvested in the summer of 2000. Model 1 had 60 features. Model 5 also had 60 features, but Tainung 67 and Taikeng 8 were considered the same cultivar. By loading in PC1, Model 2 had 50 features. Thirty-five features were selected from the correlation coefficient matrix for Model 3, from low to high. Based on the contribution from the training model, Model 4 had 20 features. The average validation rates for Models 1 to 5 were 92.2% (with 4.8% standard deviation); 91.8% (5.3%); 89.9% (6.3%); 90.6% (6.1%); and 94.6% (6.0%), respectively. Based on the three-year model, which was used to classify the fourth year samples, the average classification rates for Models 1 to 5 were 92% (with 11.0% standard deviation); 90.0% (19.7%); 91.0% (13.4%); 91.8% (15.7%); and 99.8% (0.5%), respectively. These five models had >91% average validation rates and average classification rates. However, Model 4 was considered the best model for classifying these five cultivars because it required fewer features and held a stable classification rate as it changed from 10 to 55 features.

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