Identification and Classification of Bulk Paddy, Brown, and White Rice Cultivars with Colour Features Extraction using Image Analysis and Neural Network

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Abstract

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We identify five rice cultivars by mean of developing an image processing algorithm. After preprocessing operations, 36 colour features in RGB, HSI, HSV spaces were extracted from the images. These 36 colour features were used as inputs in back propagation neural network. The feature selection operations were performed using STEPDISC analysis method. The mean classification accuracy with 36 features for paddy, brown and white rice cultivars acquired 93.3, 98.8, and 100%, respectively. After the feature selection to classify paddy cultivars, 13 features were selected for this study. The highest mean classification accuracy (96.66%) was achieved with 13 features. With brown and white rice, 20 and 25 features acquired the highest mean classification accuracy (100%, for both of them). The optimised neural networks with two hidden layers and 36-6-5-5, 36-9-6-5, 36-6-6-5 topologies were obtained for the classification of paddy, brown, and white rice cultivars, respectively. These structures of neural network had the highest mean classification accuracy for bulk paddy, brown and white rice identification (98.8, 100, and 100%, respectively).

Keywords: stepdisc analysis; HSI; HSV back propagation algorithm, bulk images

Rice (*Oryza sa*tiva L.) is one of the most consumed crops in the world. The white rice is the vital food for a large part of the world population. Different food products are made from different classes of rice, therefore the identification of the rice cultivars is one of the most important factors for consumers. The identification of the rice cultivar class is a significant quality control standard for the Iranian food grain industries. Physical parameters of the rice cultivars, including colour, size, shape, and texture, are quality indices for the inspection of bulk rice samples (Tahir *et al*. 2007).

Quality control is one of the important topics in the food industry because, after harvesting, food products are sorted and graded in different grades based on the quality parameters. Nowadays, the quality of rice is estimated intellectually and manually through visual inspection by experienced resourceful people. Manual inspection however, is time consuming; in addition, the result of this method may be not reliable due to human errors or unskilled technicians. Generally, this traditional method is exclusive, tedious, and unreliable due to its intellectual nature (Sansomboonsuk & Afzulpurkar 2008).

The rice cultivars are so similar to one another that their identification is difficult. Machine vision technology (MVT) supplies an alternative to the manual inspection of grain samples (Visen *et al*. 2004). This method is a promising technology for the quick identification and automation of grain handling. The measurement and extraction of the colour features using a machine vision system offers a potential solution to considering colour evolution as a basic objective. Machine vision is a well-established implement in automotive industry. With recent advances in the computational power and memory of personal computers, machine vision systems can be applied for online inspection of agricultural products (Choudhary *et al.* 2008).

Usually the image processing method consists of preprocessing and main processing. In the preprocessing stage, segmentation, background removal, and object detection is done. These operations are necessary for the extraction of the morphological features (main processing) and can be used for the grain cultivars classification in the automation of rail car unloading operations at grain handling facilities. In recent years, several researches have been done into the on application of computer vision systems and artificial neural networks to identify the grain. Paliwal *et al.* (2001) used eight morphological features of five different cereal grains to train diverse ANN architectures. They obtained classification accuracies of 97% for wheat and oats and about 88% for barley and rye using four layer back propagation architecture for the ANN. Zayas *et al.* (1996) studied the cultivar classification of wheat. In this study, the pattern recognition methods were applied to the data base of the combined parameters for wheat kernels of six classes and seventeen varieties of soft and hard wheat. Colour and texture features are used to develop a neural network model for the classification of different food objects like Idli, Wada, Bonda etc., as proposed in (Anami *et al.* 2005). Anami *et al.* (2003) developed a method for the classification and gradation of different grains such as Ground nut, Bengal Gram, wheat, etc.

Many researchers have used artificial neural network to identify and classify the bulk of grain samples of five grain types, namely barley, oats, rye, wheat, and durum wheat using colour and textural features, and classification accuracies of over 98% were obtained for all grain types (Visen *et al.* 2004; Anami *et al.* 2006). A method for the classification and gradation of different grains (for a single grain kernel) such as groundnut, Bengal gram, wheat etc., was described by (Anami *et al.* 2003). The determination of the potential of the morphological features to classify different grains, classes, cultivars, damaged grains, and impurities using statistical pattern recognition techniques was the main focus of many studies (Keefe 1992; Spairstein & Kohler 1995). Sapirstein and Kohler (1999) investigated the effect of sampling on the precision and accuracy of the digital image analysis of different commercial sample grades of Canada Western Red Spring (CWRS) wheat.

Some researchers examined the use of colour features for the wheat classification and identification of damaged kernels in wheat (Neuman *et al.* 1989; Luo *et al.* 1999a). Only few works were carried out to incorporate textural features (Majumdar & Jayas 2000; Anami *et al.* 2005). Many studies also used the features of colour, morphology, and texture for the identification of grains and their quality using pattern classification (Shantaiya & Ansari 2010; Anami *et al.* 2011). Visen *et al.* (2002) used morphology and colour features for classification of Canadian grains, that the best classification accuracies (98.7, 99.3, 96.7, 98.4, and 96.9 for barley, CWRS wheat, CWAD wheat, oats, and rye, respectively) having been obtained by using specialist probabilistic neural networks. Most of the previously published studies have concentrated on identifying grain types from digital images one by one. While the pattern recognition approaches for the classification of bulk grain samples can be effective and reliable, rice crop has many postharvest stages such as drying, hulling, and whitening. The safe level of the moisture content is different for each cultivar compared to the others, so the cultivar identification in drying period can help to terminate the process at a specific value of the moisture content. The determination of the moisture content of each cultivar in each stage is important. The identification of cultivars for hulling and whitening processes led to an intensive decrease in the broken rice content. Before starting the operations, the respective apparatuses should be adjusted for each cultivar. In addition, little work is cited on bulk rice images instead of single grain images in the Iranian cultivar classification. Thus, the objective of this research was to classify bulk paddy, brown, and white rice cultivars using colour features.

MATERIAL AND METHODS

The grain samples used in this research were collected from the Rice Research Institute in Amol, Iran. Five cultivars of rice widely cultivated in Iran were used in this study – cvs Fajr, Khazar, Neda, Shiroodi, and Tarom Mahali (Figure 1). These cultivars were prepared as paddy, brown, and white rice. After the preparation of the rice samples, about 2.50 kg of paddy rice of each cultivar was isolated and kept in double sealed polythene bags at 5°C in a refrigerator until the start of the experiments. All waste materials and broken rice grains were seperated from the samples manually. The moisture contents of the samples ranged between 10 and 11% (d.b).The samples were husked by a laboratory husker (THU 35, Japan) at an

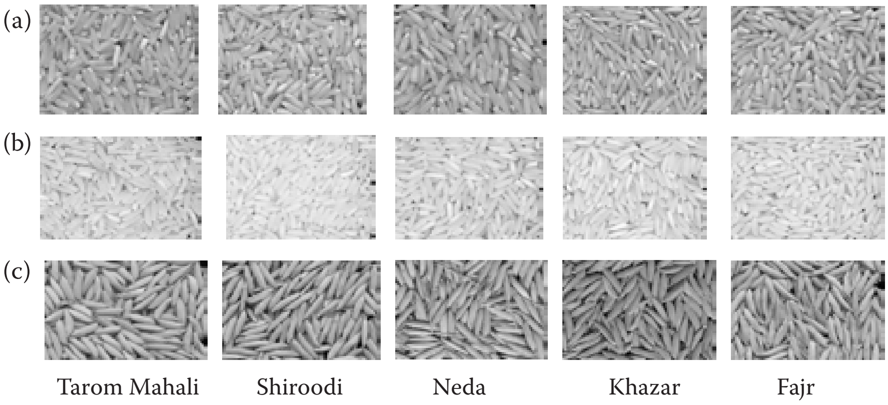

Figure 1. Used rice cultivars: (a) brown rice, (b) white rice, and (c) paddy

adequate moisture content (change of paddy rice to brown). The whitening of brown rice was carried out by a laboratory rice whitener (Setekka TM 05, Japan).

Methodology. The classification process of the rice cultivars included the image acquisition, preprocessing, feature extraction, use of neural network, and classifier using MATLAB® 2010, as explained bellow.

Image acquisition. Images of three types of products (paddy, brown and white rice) were acquired using the scanner Hp Scanjet G3110 (Hewlett-Packard Co., Beijing, China). All images had 300 dpi resolution and 540 × 390 pixels in BMP format. Accordingly, 1350 images were prepared (90 images for each type of cultivar). Every image had 3 repetitions of each rice sample.

Preprocessing. This stage consists of image segmentation and noise reduction (Figure 2). The aim of this stage was the extraction of three sub images from the main image. The preprocessing implementation is shown in Figure 3.

Colour feature extraction. An algorithm was developed for the extraction of 36 colour features of bulk rice images (Table 1). The Eqs (1) to (4) were applied to calculate the mean, variance, standard deviation, and range for all sub images (Anami *et al*. 2011).

$$\text{Mean} = \sum x x \sum y \, P(x,y) \quad (1)$$

$$\text{Variance} = \sum x,y \, P(x-\mu)^2 \, P(x,y) \quad (2)$$

$$\text{Range} = \text{Max}\,(P(x,y)) - \text{Min}\,(P(x,y)) \quad (3)$$

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu)^2} \quad (4)$$

The Hue (H), Saturation (S), Intensity (I) components of HSI colour space, and Hue (H), Saturation(S), and Value (V) of HSV colour space were extracted from

Image acquisition
↓
RGB to binary
↓
Noise reduction
↓
Centroid of object detection
↓
RGB crop based on centroid
↓
Background deletion

Figure 2. Preprocessing flowchart

Table 1. Extracted features for classification of rice

No.	Features	No.	Features	No.	Features
1	red mean	13	H_{hsi} mean	25	H_{hsv} mean
2	red variance	14	H_{hsi} variance	26	H_{hsv} variance
3	red range	15	H_{hsi} range	27	H_{hsv} std
4	red std	16	H_{hsi} std	28	H_{hsv} range
5	green mean	17	S_{hsi} mean	29	S_{hsv} mean
6	green variance	18	S_{hsi} variance	30	S_{hsv} variance
7	green range	19	S_{hsi} range	31	S_{hsv} std
8	green std	20	S_{hsi} std	32	S_{hsv} range
9	blue mean	21	intensity mean	33	value mean
10	blue variance	22	intensity variance	34	value variance
11	blue range	23	intensity range	35	value std
12	blue std	24	intensity std	36	value range

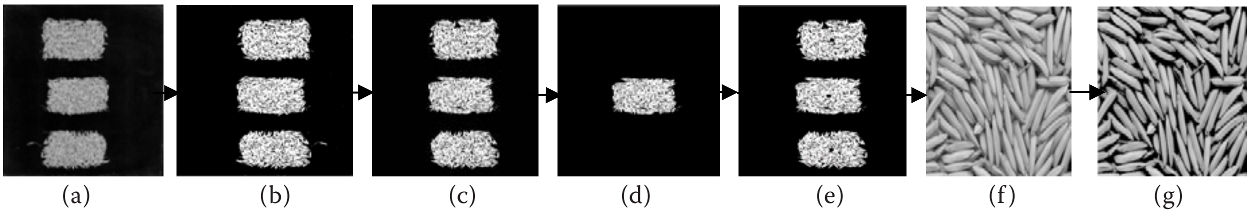

Figure 3. Preprocessing implementation process: (a) RGB image, (b) binary image, (c) noise reduction, (d) object separation,(e) centroid detection, (f) RGB image crop, and (g) background deletion

RGB components using Eqs (5) to (10) (Anami *et al.* 2011; Neelamma *et al.* 2011).

$$I = 1/3\ (R + G + B) \qquad (5)$$

$$S_{hsi} = 1 - \frac{3}{(R + G + B)}\ [\min\ (R, G, B)] \qquad (6)$$

$$H_{hsi} = \arccos \left\{ \frac{[(R - G) + (R - B)]/2}{[(R - G)^2 + (R - B)(G - B)]^{1/2}} \right\} \qquad (7)$$

$$V = \max\ (R, G, B) \qquad (8)$$

$$S_{hsv} = V - \min\ (R, G, B)/V \qquad (9)$$

$$H_{hsv} = (G - B)/6S, \text{ if } V = R$$

$$H_{hsv} = 1/3 + (B - R)/6S, \text{ if } V = G$$

$$H_{hsv} = 2/3 + (R - G)/S, \text{ if } V = B \qquad (10)$$

Neural network and classifier. Artificial neural network of MATLAB® 2010 a software was used for the classification of bulk rice. All 36 colour features were used in the training and testing of the artificial neural network. The multilayer feed forward neural network with back propagation (BP) algorithm was developed for the classification of rice cultivars as shown in Figure 4 (Anami *et al.* 2011). Firstly, a random section of data was used for the network training and the residual data was used for the testing. One and two hidden layers were implemented in the network training. Two decision indices of confusion matrix and classification accuracy were applied to identify the rice cultivars in three modes of paddy, brown, and white rice. The number of neurons in the input layer was equal to the number of properties, i.e. 36 neurons, and the output layer according to the number of cultivars was equal to the number of rice category, i.e. five neurons. A five-bit binary number represented the category of classification (10000 to Fajr, 01000 to Khazar, 00100 to Neda, 00010 to Shiroodi, 00001 to Tarom Mahali) (Figure 4).

Levenberg-Marquardt (LM) back propagation algorithm was used for the network training. The training, validation, and neural network testing were supplied using 1350 patterns (90 images for each cultivar). The network was trained and tested for 400 epochs and then applied to the validation of the data set. This epoch number was adequate to allow sufficient events before the training process was stopped. The optimised neural network was trained with the termination error (TE) = 0.01, learning rate (lr) = 0.08, and momentum coefficient (mc) = 0.6. The important features were selected by means of STEPDISC analysis and were used as neural network inputs (SAS 2004).

RESULTS AND DISCUSSION

Classification process. As shown in Table 2, the Mean classification accuracies acquired 93.3% for

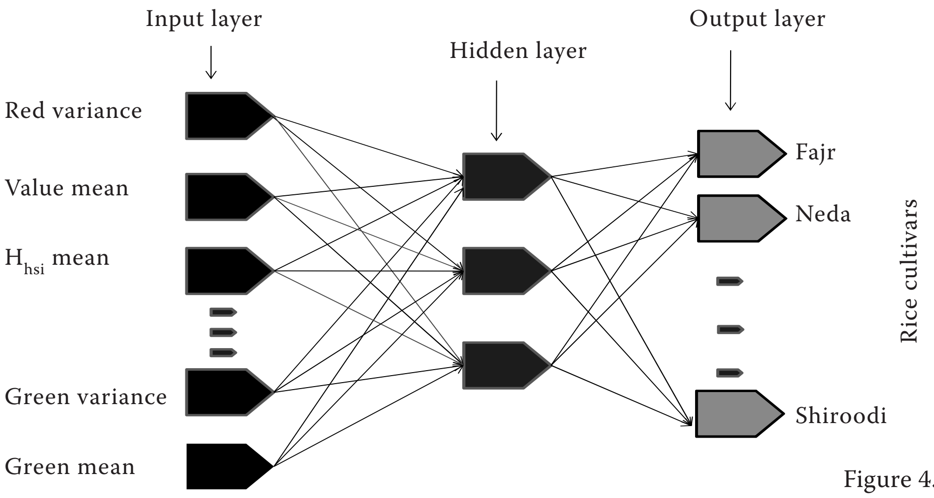

Figure 4. Structure of neural network

paddy cultivars (Fajr, Khazar, Neda, Shiroooodi, Tarom mahali) with one hidden layer of neural network, respectively. According to Table 2, after network training and simulation of the paddy data set, the results showed that the activation function of logsig with output transfer of purelin was the best structure and training algorithm of LM networks with LM training algorithm (topology of 36-24-5). Further, the activation function tansig with output transfer of logsig presented poor results for classifying of the paddy cultivars. As illustrated in Table 2, the classification results of the brown rice cultivars were better than the classification of paddy cultivars because the mean classification accuracy of brown rice acquired 98.9% with the activation function of logsig and output transfer of tansig (topology 36-7-5). The results of neural network for white rice cultivars classification are better than the results of paddy and brown rice classification because the classification accuracy was 100% for all cultivars (topology 36-5-5). The highest classification accuracy for paddy was obtained with topology of 36-6-5-5 and two hidden layers. The number of neurons in the first and second layers was 6 and 5, respectively. The mean classification accuracy of paddy cultivars for data set testing acquired 98.8%. The classification accuracy of these cultivars with the optimised network and two hidden layers showed great similarity compared to the results of the optimised network with one hidden layer.

Table 2. The best topologies for classification of paddy, brown and withe rice cultivars

Transfer function	Topology	Iteration	Mean classification accuracy (%)
Paddy cultivar			
Logsig-purelin	36-24-5	25	93.3
Tansig-purelin	36-23-5	14	91.1
Purelin-purelin	36-24-5	5	88.9
Purelin-logsig	36-14-5	126	83
Logsig-logsig	36-25-5	199	63
Tansig-logsig	36-18-5	196	60
Brown rice cultivar			
Logsig-purelin	36-7-5	22	98.9
Purelin-tansig	36-6-5	11	97.8
Purelin-purelin	36-22-5	55	95.6
Purelin-logsig	36-20-5	43	94.4
Logsig-logsig	36-16-5	123	47.8
Tansig-logsig	36-20-5	180	34
White rice cultivar			
Logsig-purelin	36-5-5	13	100
Tansig-tansig	36-6-5	11	98.9
Logsig-tansig	36-9-5	7	97.8
Purelin-tansig	36-10-5	7	95.6
Purelin-purelin	36-5-5	7	93.3
Purelin-logsig	36-8-5	189	91.1
Logsig-logsig	36-16-5	7	56.7
Tansig-logsig	36-18-5	7	54.4

To establish suitable topology, several neurons were placed in different layers for classification of brown rice cultivars. The result showed that the topology of 36-9-6-5 was the best one for identifying the brown rice cultivars. Thus, the highest average classification accuracy for this topology was 98.8%. After training and testing the networks with two hidden layers and different neurons, the highest mean classification accuracy acquired 100% with topology 36-6-6-5 in the identification of white rice cultivars. This result is equal to the results of the network with one hidden layer with the mean classification accuracy equal to 100%. For the simplification of the network, the network with one hidden layer is suggested to identify these cultivars. These results were similar in the detection of phalaenopsis seeding diseases using colour and textural features by Yi (2007).

Feature selection. Several colour features had great effects on the cultivar classification. If one of these properties is selected to identify the cultivars, other features have no significant effect on the identification of improvement. Hence, some of them are unnecessary features. In order to study the importance level of the colour features, the STEPDISC analysis was used (Paliwal *et al.* 2004; Yan *et al.* 2005) to select the significant features.

Colour feature models for paddy. According to correlation coefficient of paddy, 13 features were selected in the classification model, because they were significant to the classifier. The selected features were arranged based on the decreasing level of the contribution in the classification model (Table 3). This was because the excessive number of features adversely affects the classifier by introducing redundancies and increasing the complexity (Luo *et al.* 1999b). As a result, a useful feature may get overshadowed by other features and may not contribute very much in the presence of certain input features.

The blue mean was the most important colour feature (average squared canonical correlation, ASCC = 0.191) and the average of intensity was not an important feature (average squared canonical correlation, ASCC = 0.681).

Discriminant analysis was implemented with 5, 10, and 13 features. The mean classification accuracy

Table 3. STEPDISC analysis for the best colour features of paddy, brown and white rice

No.	Features	Average Squared Canonical Correlation (ASCC)	Partial r^2	No.	Features	Average Squared Canonical Correlation (ASCC)	Partial r^2
Paddy rice				19	red variance	0.826	0.0638
1	blue mean	0.191	0.7642	20	H_{hsv} variance	0.829	0.0418
2	green mean	0.293	0.8625	21	blue std	0.829	0.0392
3	S_{hsv} mean	0.457	0.8324	22	intensity variance	0.834	0.0852
4	S_{hsi} mean	0.626	0.6911	23	S_{hsv} variance	0.836	0.0547
5	H_{hsv} mean	0.643	0.3086	24	value variance	0.840	0.0214
6	H_{hsi} mean	0.662	0.4260	25	value mean	0.845	0.1191
7	S_{hsv} variance	0.668	0.2924	**White rice**			
8	intensity variance	0.674	0.3025	1	blue mean	0.229	0.9160
9	green variance	0.675	0.0417	2	S_{hsi} mean	0.370	0.5726
10	blue range	0.678	0.0323	3	H_{hsv} mean	0.421	0.4562
11	S_{hsi} variance	0.679	0.0244	4	Red mean	0.471	0.6047
12	S_{hsv} range	0.680	0.0187	5	S_{hsv} mean	0.512	0.2136
13	intensity mean	0.681	0.0177	6	S_{hsv} variance	0.551	0.1950
Brown rice				7	S_{hsi} std	0.559	0.2386
1	H_{hsi} mean	0.170	0.6817	8	green mean	0.592	0.1352
2	value Std	0.217	0.5718	9	H_{hsi} mean	0.613	0.2126
3	red mean	0.318	0.4925	1	H_{hsv} variance	0.633	0.1100
4	green mean	0.489	0.9121	11	S_{hsi} variance	0.642	0.1145
5	blue mean	0.540	0.3726	12	S_{hsi} range	0.656	0.0786
6	S_{hsv} mean	0.657	0.7654	13	H_{hsi} variance	0.666	0.0596
7	H_{hsv} mean	0.688	0.2632	14	blue variance	0.670	0.0546
8	S_{hsi} mean	0.772	0.4436	15	S_{hsv} std	0.677	0.0437
9	S_{hsv} std	0.785	0.2393	16	value range	0.679	0.0396
10	S_{hsi} range	0.790	0.0717	17	value variance	0.681	0.0396
11	S_{hsv} range	0.794	0.0782	18	intensity variance	0.686	0.0647
12	S_{hsi} std	0.801	0.0673	19	blue std	0.690	0.0491
13	H_{hsv} std	0.804	0.9210	20	green variance	0.694	0.0447
14	S_{hsi} variace	0.811	0.0797	21	value mean	0.698	0.0420
15	H_{hsi} variance	0.815	0.0845	22	red range	0.701	0.0282
16	intensity std	0.816	0.0649	23	red variance	0.703	0.0390
17	blue variance	0.818	0.0773	24	green std	0.706	0.0253
18	H_{hsi} std	0.821	0.0791	25	intensity std	0. 710	0.0532

was calculated with all 36 features. After the feature selection, the mean classification accuracy using the first five features was poor (Figure 5). The mean accuracy – for paddy classification with the first five features was acquired 61.11%. The level of features contribution (see ASCC values) beyond the first 5 features was poor (Table 3).

When all of 13 features were used, the mean accuracy was 96.66%. It was the highest accuracy in the identification of paddy cultivars. Also, with the first ten features, the mean classification accuracy acquired was 95.66%. Using 10 and 13 features, the mean classification accuracies were higher than the mean classification accuracies using 36 features (Figure 5). This result showed that only the first 13 features should be used. Classifying bulk paddy using the first 10 colour features instead of 36 features would save computational time. These results resemble those of Majumdar and Jayas (1999).

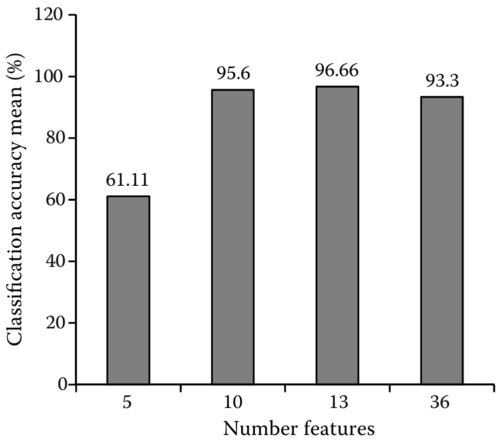

Figure 5. Classification accuracies of bulk paddy samples using input of different features

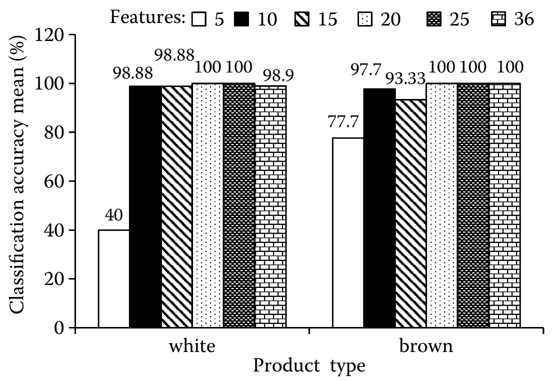

Figure 6. Classification accuracies of bulk brown and white rice samples using input of different features

Colour feature models for brown rice. Table 3 shows the ranking of colour features for brown rice bulk. After STEPDISC analysis for the feature selection, the hue mean was the most significant feature in circuits of level contribution (average squared canonical correlation, ASCC = 0.170), and the value of mean feature was the least significant feature (average squared canonical correlation, ASCC = 0.845), because they were highly correlated. The STEPDISC analysis was carried out to determine the level of contribution of each colour feature of brown rice bulks to the colour model so that al1 the redundant features could be eliminated.

The results show, that, after the colour feature selection of all 36 features using STEPDISC analysis, six features of the selected parameters were reported by Majumdar and Jayas (1999). The mean classification accuracy of brown rice with the first five features was (77.7%). The mean accuracy with both of 20 and 25 features were acquired 100%. But with 10 and 15 features, the mean accuracies were earned 97.77% and 93.33 %, respectively (Figure 6).

Colour feature models for white rice. Table 3 reveans that the number of features had a significant effect on improving the classification accuracy of the cultivars. The 25 features of the 36 extracted colour features were selected and ranked according to their contribution to the discriminatory powers of the corresponding feature model. The colour features were quite powerful in discriminating the classification of white rice cultivars.

The blue mean feature with minimum (ASCC = 0.229) was selected as the most important feature and it played a vital role in the classification of bulk rice cultivars. The saturation mean became the second most important feature with ASCC = 0.370 (Table 3). This was because of the STEPDISC analysis process where first the most significant features were selected (for example, blue mean), then the rest of the features were selected depending on their correlation with the features already being selected. Also, the significant difference between the means was the most important feature for these five cultivars.

The mean classification accuracies were very low (40%) for the first five features while they were very high (100%) for both 20 and 25 features (Figure 6). Majumdar and Jayas (1999) reported the classification accuracy close to 100% using images of bulk samples. For all discussed models, with an increase in the number of features, the classification accuracies increase to a certain extent and then they remain constant or gradually decrease in analogy with the study conducted by Petersen (1992) on the identification of weed seeds by shape and textural analyses.

CONCLUSIONS

This study proved that the image analysis can be used to classify the rice cultivars as a new approach using colour features extraction of bulk grain images instead of single grain images. The classification accuracy obtained using different input feature sets for paddy, brown, and white rice cultivars was over 92%. In the classification of paddy cultivars the best results were obtained using the neural network with two hidden layers with topology 36-6-5-5, and the highest classification accuracy being 98.8%. Also brown rice and white rice cultivars could be classified with close to 100% classification accuracy using just the 20 first features set.

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