

# **Bulk Paddy Grain Ageing Period Classification using RGB and HSI Color Features**

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## **ABSTRACT**

Paddy (rough rice) grain age assessment is one of the requirements in the rice industry as it has significant effects on processing and quality of products. This paper presents a color based approach for the classification of fifteen leading paddy varieties and their ageing periods from their bulk grain sample images. Five different ageing periods are considered, namely, 1, 3, 6, 9 and 12 months. Since color changes are observed with ageing, the features from RGB and HSI color spaces are used in the classification. The performance based feature reduction technique is adopted for feature reduction. The average ageing period classification accuracies of 93.60%, 92.40%, 91.87%, 93.33% and 94.13% are obtained for ageing periods of 1,3,6,9 and 12 months respectively across the varieties using BPNN. The work finds application in automated pricing and grading, decision on suitability for value added products in food industry, developing a machine vision system in agriculture produce market (APMC) etc.

## **General Terms**

Image classification, Pattern Recognition

## **Keywords**

Rice, Age assessment, Husk color, stored food grains, BPNN.

## **1. INTRODUCTION**

Paddy is the most important domesticated cereal of Asia covering about one-fourth of the total cropped area and feeds half the world. The paddy crop is grown throughout the year, at best twice in a year. Whereas in tropical regions, paddy is frequently harvested in a year and due to the extreme environmental conditions, it usually stored for a short period. But being the staple food of humankind, it is required all the year round. Therefore, the paddy grains have to undergo long storage for up to a year or more like other cereal grains. Paddy grains immediately after harvest are normally a natural golden yellowish in color but in storage they usually discolor. During the storage, paddy grains undergo several physicochemical and physiological changes [16]. The physicochemical properties include in starch changes, fat oxidation, changes in cell walls and protein. The physiological properties include all the external characteristics, such as size, shape, color and smoothness. The knowledge of physiological properties of paddy is very much necessary in all the activities from harvesting, drying, storage, milling, packaging, marketing, cooking, product making and utilization.

Storage-induced ageing of paddy grains has both desirable and undesirable effects on the end product depending on the storage conditions and varieties. Rice (milled paddy) is a unique food crop among other food grains in that it undergoes significant change in its organoleptic cooking and eating behavior with the progress of time during storage. Soon after harvest, rice tends to cook generally sticky, lumpy and moist

mass. This character gradually changes over time. After six months of storage, rice cooks comparatively more dry, soft and free flowing. Thus, aged rice is preferred in testing for milling and cooking properties. Bran oil, wine and vinegar are the other end products of aged paddy. This pattern of usage results in the need to store paddy over varying periods and peoples' preference varies for fresh or aged paddy based on the end products. Ageing profoundly affects consumer acceptance and processing behavior of paddy grains. Also it can improve the quality of paddy grains and widens the marketability. In fact, there is a substantial price differential between new and old paddy and people are happy to pay a higher price for old paddy. So a proper paddy grain age assessment technique is necessary for consumers and traders for domestic use as well as the traders for their commercial use.

One of the most sensitive indices of the ageing process in paddy grains is the change in husk color or discoloration of husk (paleo or seed coat) due to pH, free fatty acids and enzyme activities. This forms the basis for the present work. The trained personnel visually observe the husk color to determine the grain age. This visual inspection is subjective and tedious by nature. An objective, rapid and automatic grain age assessment system would be beneficial to the potential farmers and consumers in getting the right aged paddy grains.

To know the state-of-the-art in automation of grain age assessment in the field of food grains, a survey is made and the gist of a survey is given as under.

Azman [2] proposed the potential of color indices to determine the moisture content and maturity stage of paddy using color properties extracted from RGB and thermal images. Five color indices such as Red Index, Green Index, Blue Index, Thermal Red Index and Thermal Index are used to analyze the maturity stage and moisture content. Red index gave the best model of paddy maturity and moisture content estimation compared to other color indices with 99.2% and 99.1% percentage of successful estimation, respectively. Azman [4] presented a new technique of paddy maturity estimation using seven color indices extracted from RGB color space. The color indices are Red, Green, Blue, difference between Green and Blue, difference between Green and Red, Green to Blue Ratio, and Green to Red Ratio. The results showed that the color indices gave significant correlation with the maturity stage of paddy. Haw [5] proposed the color vision methodology to determine Malaysian paddy grain maturity from the hue color and weight of the florets.

Site [6] presented an image processing technique to identify mature and immature paddy grains using mean, median, standard deviation and Otsu features extracted from segmented images. Golpour [7] proposed an image processing algorithm for classification bulk paddy, brown and

white rice of five rice cultivars using 36 color features in RGB, HIS and HSV color spaces. The backpropagation neural network was used for classification and obtained mean classification accuracy of 96.66% with 13 color features. Khongsak [9] applied chemiluminescence system to analyze the color of chemical solutions changed with regards to the age of rice grains.  $L^* a^* b^*$  color space was employed to determine the color bands of fresh and aged rice grains. Liu [10] proposed an image processing method to detect the color of fresh and old rice using RGB and HSI color models and concluded that the fresh rice is brighter than the old rice. Maturada [13] proposed a rice quality evaluation method using HSI color space to evaluate various kernel defects, including kernel discolorations and chalkiness. Xiaoli [14] presented Chemometrics method coupled with on visible/near infrared (Vis/NIR) reflectance spectroscopy for discriminating paddy seeds stored for four different ageing periods namely one, two, three and four years. A total of 210 samples of paddy seeds, which belonged to four classes were used for collecting Vis/NIR spectra. The spectral data was processed and analyzed using wavelet transform. The feature reduction was performed using principal component analysis (PCA). ANN with backpropagation model was used for ageing period discrimination and obtained accuracy rates of 100%, 100%, 100%, 90% for the selected four ageing periods respectively. The mean discrimination accuracy rate of 97.5% was achieved using eight principal component features. Nambi [3] proposed a scheme for the evaluation of color behavior during ripening of mango using RGB color measurements. The changes in RGB values in each day during ripening were recorded and it was found that the ripening days significantly influence the color change. The changes in red ratios (R/G, R/B), green ratios (G/R, G/B) and blue ratios (B/R, B/G) were calculated and used to predict the ripening. Belovic [8] proposed a color change evaluation technique for paprika powder during storage from its surface color using CIE  $L^*a^*b^*$  color space. The change of reflected color of paprika powder during three years of storage was characterized by increase of  $L^*$  (lightness) and  $b^*$  (yellowness) color values and decrease of  $a^*$  (redness) color value. Effendi [11] developed a grading method to classify *Jatropha Curcas* fruit into raw, ripe and overripe by analyzing surface color. Backpropagation neural network was used in the classification process and obtained an accuracy of about 95%. Ali [12] proposed classification of hard wheat, tender wheat and barley using morphological, color and wavelet features with the help of ANN classification method with the best recognition rate of 98%. Visen [15]; Majumdar and Jayas [17], Majumdar and Jayas [18] proposed a method for identifying bulk cereal grains using color features.

From the literature survey, it is observed that Xiaoli [1] has presented Chemometrics method coupled with on visible/near infrared (Vis/NIR) reflectance spectroscopy for discriminating paddy seeds stored for four different ageing periods namely one, two, three and four years. Only four varieties are considered and limited number of samples are used in the work. It is also observed in consultation with experts that, a rapid change in paddy husk color occurs during the first year of natural storage and the husk color change is more gradual after one year. This is the motivation for the present work.

Some works are also being carried out for classification of husked paddy (rice kernel) grains into fresh and old based on color indices, while certain studies have been made on using image analysis to discriminate paddy varieties based on shape and color features. Few works have been reported on using image analysis to evaluate various rice kernel defects and

chalkiness. To the authors' knowledge, there is scope for classification of ageing periods from bulk paddy grain images, considering more varieties and more samples.

The remaining part of the paper is organized into five sections. Section 2 gives the description of the proposed methodology. Section 3 gives the explanation of image dataset preparation. Section 4 presents the variety recognition methodology from bulk paddy grain sample images. Section 5 gives the description of the process of ageing period classification, summary of the results with concluding remarks and suggestions for future scope.

## 2. PROPOSED METHODOLOGY

The proposed methodology consists of two main phases. The first phase is for variety recognition, where paddy variety is identified. The second phase is for classification of ageing periods, where selected five ageing periods in months are predicted. The block diagram illustrating the steps involved in the proposed methodology is shown in Fig 1.

## 3. IMAGE DATASET

In consultation with the University of Agricultural Sciences (UAS), Dharwad, Karnataka State, India, fifteen certified and popular paddy varieties are selected as grain samples in the work. The matured and disease free paddy varieties are obtained from Agricultural Research Station, Mugad, Dharwad. These varieties are grown in different parts of Karnataka, India. The paddy grain samples are cleaned with an air-screen cleaner to remove all foreign matter such as dust, dirt, stones, chaff, immature and broken seeds and packed in polyethylene bags before analysis. The names of the paddy varieties considered in the work are Abhilasha, Bhagyajyothi, Buddha, Intan, Jaya, Jayashree, Mugad Dodiga, Mugad Sughand, Mugad 101, Mugad Siri, PSB 68, Rajkaima, Redjyothi, Thousand One and Thousand Ten.

Images of bulk paddy grain samples from fifteen paddy varieties at five different ageing periods are acquired. The image data set used for the experimentation comprises 7500 images, considering 500 images (100 images per ageing period) from each of the paddy varieties. Freshly harvested paddy grains of one month old are considered in the first ageing period. In the second, third, fourth and fifth ageing periods, paddy grains aged at three, six, nine and twelve months old are considered respectively.

The images are captured under standard lighting conditions using color camera PENTAX MX-1, USA, having resolution of 14 mega pixels. The camera has a zoom lens of 10-120 mm focal length and a 72 mm close-up lens set. The camera is vertically oriented and approximately a distance of 0.5 meters is maintained while capturing the images. The acquired images of size 1920 X 1080 pixels are cropped to size 400 X 400 pixels for the reasons of reduction in computational overhead and storage requirements in order to achieve easier training. The images of selected paddy varieties at five different age intervals are shown in Table 1.

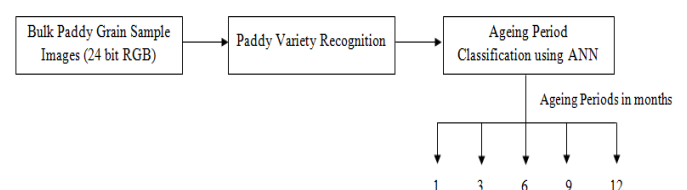


Fig 1. Block diagram of the proposed methodology

#### 4. VARIETY RECOGNITION

In this phase, an edge texture features based methodology is employed to recognize the paddy varieties [1]. Because variation in shape or texture properties of bulk paddy grains due to ageing is negligible for the considered fifteen paddy varieties and five ageing periods. The edge images required for the variety recognition process are obtained using maximum gradient edge detection method. The average paddy variety recognition accuracy of 87.80% was obtained for the reduced eight texture features. The output of this phase is given to the second phase as one of the inputs for the classification of ageing periods. However, the authors are currently working on improving the variety recognition accuracy.

#### 5. AGEING PERIOD CLASSIFICATION

Paddy husk (seed cover) color is an important visual attribute used in ageing period classification and its color varies from variety to variety. The ageing induces discoloration of husk. So, the color based methodology has been employed for the classification of the ageing periods. This phase is composed of following four stages, namely feature extraction, feature reduction, classification of ageing periods and discussion of results.

##### 5.1 Color feature extraction

Varietal differences and grain ageing for several paddy varieties can be easily classified using color information. The paddy grain husk color is an influential feature and strongly correlates with ageing. So it is used as a descriptor in classification of ageing periods from bulk paddy grain sample images. The bulk paddy grain images captured at different periods of ageing offer a tremendous amount of spatial resolution and color differences, which can be used to quantify the color distribution. To study the extent of color differences, the RGB and HSI color spaces are used and the characterization of the images is done through a series of RGB histograms. The histograms of the RGB pixel data distribution in bulk paddy grain sample images captured at five ageing periods clearly show the presence of different density distribution of RGB color primaries. It clearly states that the Red, Green and Blue color components can be quantified and the feature values can be easily used for discriminating analysis. To extract the color features independent of external illumination RGB color space is converted to HSI color space. The color features of HSI color space are combined with RGB color space features to analyze the color intensity and match actual human eye color sensitivity in ageing period classification.

The following method is adopted in extracting color features from the RGB images of bulk paddy grain. The primary step is the separation of Red (R), Green (G) and Blue (B) channels from the original color images. The next step is to extract Hue (H), Saturation (S) and Intensity (I) components from the RGB channels using the equations (1) through (3). In the further step the global color features such as mean, standard deviation, median and range are computed from all the individual R, G, B, H, S, and I color components using equations (4) through (10). A total of twenty four color features is extracted from the bulk paddy grain sample images and the features are listed in Table 2. The graphical representation of color feature values for a paddy variety Abhilasha is shown in Fig 2.

$$H = \cos^{-1} \left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[ \frac{(R-G)^2 + (R-B)(G-B)}{2} \right]^{\frac{1}{2}}} \right\} \quad \dots \quad (1)$$

$$S = I - \frac{3}{(R+G+B)} [\min(R,G,B)] \quad \dots \quad (2)$$

$$I = \frac{1}{3}(R+G+B) \quad \dots \quad (3)$$

$$\text{Mean } (\mu) = \frac{1}{N} \sum_{i=1}^N x_i \quad \dots \quad (4)$$

Where N is the total number of pixels,  $x_i$  is the  $i^{\text{th}}$  pixel value.

$$\text{Standard Deviation } (\sigma) = \frac{1}{N} \sum_{i=1}^N \sqrt{(x_i - \mu)^2} \quad \dots \quad (5)$$

Median is the middle value of the histogram. If N is odd,

$$\text{Median } (m) = \text{Pixel value of } \left( \frac{N+1}{2} \right)^{\text{th}} \text{ pixel} \quad \dots \quad (6)$$

If N is even,

$$\text{Median } (m) = \text{Pixel value of } \frac{1}{2} \left\{ \left( \frac{N}{2} \right)^{\text{th}} \text{ pixel} + \left( \frac{N+1}{2} \right)^{\text{th}} \text{ pixel} \right\} \quad \dots \quad (7)$$

Maximum element and minimum elements of the given input color (RGB) image is calculated using Equation (8).

$$\max 1 = \max (\text{image}), \max 2 = \max (\max 1) \quad \dots \quad (8)$$

The above function returns the row vector containing the maximum element from each column. Similarly, find the minimum element from the whole matrix using Equation (9).

$$\min 1 = \min (\text{image}), \min 2 = \min (\min 1) \quad \dots \quad (9)$$

Range is the difference between the maximum and minimum elements and is given in the Equation (10).

$$\text{Range} = \max 2 - \min 2 \quad \dots \quad (10)$$

##### 5.2 Performance based color feature reduction

In the present case, there are twenty four color features extracted from the images of bulk paddy grain. Some of them may be redundant and highly correlated. So, it is therefore, necessary to eliminating such color features thereby constructing effective reduced feature set which leads to satisfactory classification results. In order to improve the ageing period classification accuracy results, a performance based feature reduction process is performed. In this process the average ageing period estimation performance of individual color feature for all the paddy varieties is evaluated and then threshold based feature reduction operation is performed by considering the average ageing period classification accuracies of all the color features. The reduced feature sets are constructed from the color features whose individual average classification accuracies are equal or greater than the decided performance threshold value. The classification accuracies of all the individual color features are given in Table 4. From Table 4, the highest and lowest average ageing period classification accuracies of 54.70% and 15.46% are obtained for individual color features Red Mean and Blue Range respectively.

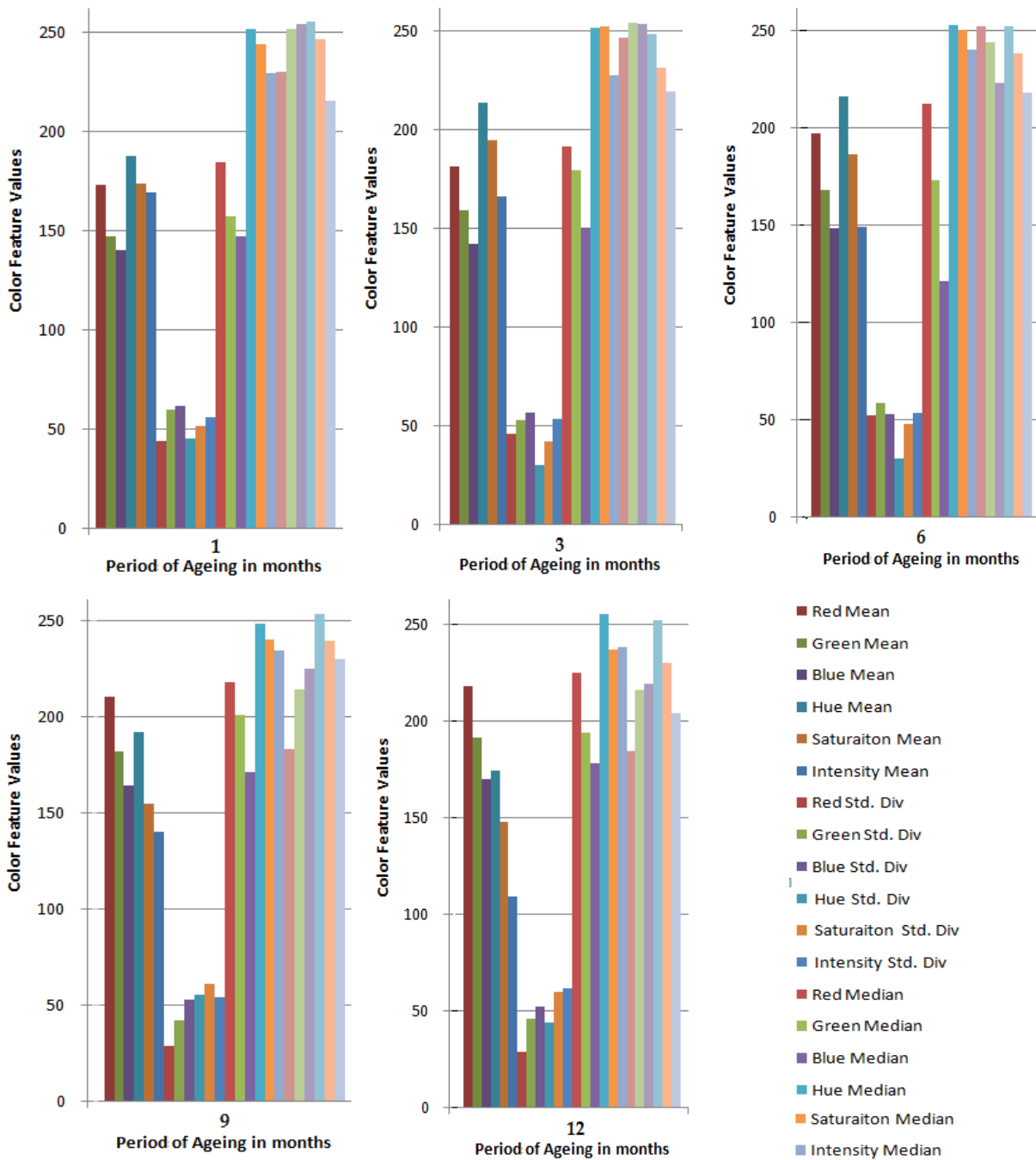


Fig 2. Graphical representation of color feature values of the paddy variety Abhilasha at five different ageing periods.

The initial performance threshold value is empirically determined as 25% and it is incremented by 5% every time to construct new reduced feature sets. Based on the classification results from Table 4, three different reduced color feature sets are constructed by setting three different performance threshold values and the summary of all reduced feature sets is given in Table 5. These reduced feature sets are then used for training and testing BPNN to perform classification of ageing periods from bulk paddy sample images.

A separate training and testing are carried out for the reduced feature sets R1, R2 and R3. The summarized ageing period classification results using reduced feature sets are given in Table 6. From Table 6, the results show that the reduced feature set R2 outperforms the other reduced feature sets R1,

R3 and the full feature set with all the color features. The maximum and minimum average ageing period classification accuracies of 93.07% and 81.49% are obtained for the reduced feature sets R2 and R3 respectively.

The color features in reduced color feature set R2 are given in Table 7. The detailed classification summary of ageing periods for all the paddy varieties using reduced color features from R2 is given in Table 8. From Table 8, the maximum and minimum average ageing period classification accuracies of 94.40% and 91.87% are obtained for ageing periods 12 and 6 months respectively. The average classification accuracy of 93.07% is achieved from all the ageing periods.

### 5.3 Classifier

Multilayer Backpropagation Neural Network (BPNN) has been used as a classifier for the present work. The number of neurons in the input layer is set to the number of appropriate color features selected as input and the output layer is set to the number of ageing periods of all the fifteen paddy varieties considered i.e. 75 (5 ageing periods for each of the fifteen paddy varieties). Levenberg-Marquardt (LM) backpropagation algorithm is used for the training. The termination error (TE) is set to 0.01, learning rate ( $\eta$ ) is set to 0.05 and momentum coefficient ( $\mu$ ) is set to 0.6. The sigmoid activation functions are used in the hidden layers. The network is trained and tested for 1000 epochs. With these parameters, the classifier is trained and tested using images of bulk paddy grain from fifteen paddy varieties captured at five different ageing periods. The sample images are divided into two halves and one half is used for training and other is used for testing. The color features are used to train and test neural network model. The percentage accuracy of ageing period classification is defined as the ratio of correctly classified sample images to the total number of sample images considered.

### 5.4 Results and discussion

In the proposed methodology, a total of 7500 images from fifteen paddy varieties captured at five different periods of ageing (100 images per ageing period per paddy variety) are considered. Out of these, 3750 images are used for training the BPNN and remaining 3750 images are used for testing.

Classification experiments have been carried out for ageing period classification using color features extracted from the images of bulk paddy grain samples. Initially, twenty four color features extracted from RGB and HSI color spaces are used to train and test the BPNN and obtained average ageing period classification accuracy of 71.55%. To improve the accuracy result, a performance based feature reduction method is employed. Ten reduced color features from RGB and HSI color spaces yield very good average ageing period classification accuracy of 93.07%.

The overall ageing period classification accuracy of the proposed method is analyzed by drawing the confusion matrix. The confusion matrix of the present work is given in Table 9 (Assuming paddy variety recognition accuracy is 100%). From the confusion matrix, among all the 3750 images, the ageing periods from 3493 images are correctly classified, thus resulted in an overall accuracy of 93.15%.

A total of 750 images from all fifteen paddy varieties captured at five different periods of ageing are subjected for expert classification and obtained ageing period classification accuracy of 98.5%. The classification results of the proposed work are compared with the similar work reported [1] and the improvements are listed in Table 10. However, the authors could not make an exact comparison due to many differences in the two approaches. The experimental results have shown that the color features from RGB and HSI color spaces are suitable for classification of ageing periods from bulk paddy grain sample images.

### 5.5 Conclusion

In the proposed methodology, the classification of ageing periods of bulk paddy grain samples from fifteen paddy varieties using image processing techniques is effectively executed. The color features from Red, Green, Blue, Hue and Intensity color planes are significantly related to the ageing of bulk paddy grains. The experimental results show that ageing

periods for bulk paddy grain are fairly estimated using reduced RGB and HSI color features. The proposed methodology has yielded promising results with the average ageing period classification accuracy of 93.07% for all the fifteen bulk paddy grain sample images acquired at five different periods of ageing.

The work finds application in automated pricing and grading, decision on suitability for value added products in the food industry, developing a machine vision system in the agricultural produce markets (APMC) etc. The generality of the proposed methodology can make it applicable in a wide range of computer vision tasks in the field of grain handling and food industry. The work is complex and challenging in terms of high irregularity in an outdoor environment. Effects of storage conditions on the classification of ageing periods can be the factor for further studies.

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## 7. APPENDIX

**Table 1. Bulk paddy grain images in five different ageing periods.**

Sl. No.	Paddy variety	Paddy Grain Age				
		1 Month	3 Months	6 Months	9 Months	12 Months
1.	Abhilasha					
2.	Bhagyajyothi					
3.	Budda					
4.	Intan					
5.	Jaya					
6.	Jayashree					
7.	Mugad Dodiga					
8.	Mugad Sughand					

**Table 1. Bulk paddy grain images in five different ageing periods (Continued...).**

Sl. No.	Paddy variety	Paddy Grain Age				
		1 Month	3 Months	6 Months	9 Months	12 Months
9.	Mugad 101					
10.	Mugad Siri					
11.	PSB 68					
12.	Rajkaima					
13.	Redjyothi					
14.	Thousand Ten					
15.	Thousand One					

**Table 2: RGB and HSI color features.**

Sl. No.	Color feature	Sl. No.	Color feature	Sl. No.	Color feature
1	Red Mean	9	Blue Mean	17	Saturation Mean
2	Red Standard Deviation	10	Blue Standard Deviation	18	Saturation Standard Deviation
3	Red Median	11	Blue Median	19	Saturation Median
4	Red Range	12	Blue Range	20	Saturation Range
5	Green Mean	13	Hue Mean	21	Intensity Mean
6	Green Standard Deviation	14	Hue Standard Deviation	22	Intensity Standard Deviation
7	Green Median	15	Hue Median	23	Intensity Median
8	Green Range	16	Hue Range	24	Intensity Range

**Table 3. Ageing period classification results using twenty four color features.**

Sl. No	Paddy variety	Classification accuracy per ageing period (%)				
		1 Month	3 Months	6 Months	9 Months	12 Months
1	Abhilasha	72	66	74	68	66
2	Bhagyajyothi	68	70	78	64	68
3	Budda	70	68	70	66	68
4	Intan	72	72	66	68	70
5	Jaya	74	72	78	72	72

6	Jayashree	60	76	76	74	76
7	Mugad Dodiga	68	68	72	66	74
8	Mugad Sughand	70	76	70	82	70
9	Mugad 101	72	66	68	80	72
10	Mugad Siri	70	76	68	72	66
11	PSB 68	74	72	74	70	68
12	Rajkaima	72	72	80	68	60
13	Redjyothi	76	78	78	76	78
14	Thousand Ten	78	68	78	74	72
15	Thousand One	66	72	74	70	78
<b>Average ageing period classification accuracy (%)</b>		70.80	71.47	73.60	71.33	70.53

**Table 4: Performance of individual color feature in ageing period classification.**

Sl. No	Color feature with feature identifier	Classification accuracy per ageing period (%)					Average classification accuracy (%)
		1 Month	3 Months	6 Months	9 Months	12 Months	
1	Red Mean (F1)	56.70	55.80	52.40	49.88	58.70	54.70
2	Red Standard Deviation (F2)	46.60	49.20	56.30	51.20	40.20	48.70
3	Red Median (F3)	23.32	22.34	32.11	29.50	31.23	27.70
4	Red Range (F4)	20.54	23.26	24.23	22.35	28.25	23.73
5	Green Mean (F5)	38.30	49.40	48.50	47.70	49.90	46.76
6	Green Standard Deviation (F6)	34.50	38.40	42.10	34.20	46.30	39.10
7	Green Median (F7)	14.50	16.40	17.40	10.20	21.30	15.96
8	Green Range (F8)	13.20	14.20	15.20	17.90	19.50	16.00
9	Blue Mean (F9)	43.40	41.50	51.80	42.50	40.20	43.88
10	Blue Standard Deviation (F10)	41.10	30.60	40.50	43.50	36.90	38.52
11	Blue Median (F11)	18.60	15.60	11.50	20.40	27.60	18.74
12	Blue Range (F12)	17.20	23.30	10.60	7.50	18.70	15.46
13	Hue Mean (F13)	49.00	43.60	43.60	42.84	36.03	43.01
14	Hue Standard Deviation (F14)	37.71	36.56	38.85	35.90	38.68	37.54
15	Hue Median (F15)	25.40	20.30	23.30	21.34	25.32	23.13
16	Hue Range (F16)	17.80	20.20	22.43	23.30	26.40	22.03
17	Saturation Mean (F17)	12.30	16.60	21.33	19.80	21.45	18.30
18	Saturation Standard Deviation (F18)	29.17	29.47	30.43	28.56	31.48	29.82
19	Saturation Median (F19)	19.76	22.09	24.73	23.89	26.44	23.38
20	Saturation Range (F20)	19.40	29.80	31.67	29.82	32.46	28.63
21	Intensity Mean (F21)	33.30	32.58	34.99	32.53	35.34	33.75
22	Intensity Standard Deviation(F22)	32.78	36.45	32.30	28.70	31.20	32.29
23	Intensity Median (F23)	24.18	27.12	28.89	27.09	29.86	27.43
24	Intensity Range (F24)	22.68	26.07	27.79	26.12	28.88	26.31



**Table 5. Reduced color feature sets obtained by performance based feature reduction method.**

Sl. No	Performance threshold (%)	Reduced feature set	Reduced feature set size	Reduced feature set identifier
1	25	F1, F2, F3, F5, F6, F9, F10, F13, F14, F18, F20, F21, F22, F23, F24	15	R1
2	30	F1, F2, F5, F6, F9, F10, F13, F14, F21, F22	10	R2
3	35	F1, F2, F5, F6, F9, F10, F13, F14	8	R3

**Table 6. Ageing period classification results of three reduced color feature sets.**

Sl. No	Reduced feature set identifier	Ageing period in months	Average ageing period classification accuracy per ageing period (%)	Average ageing period classification accuracy (%)
1	R1	1	83.07	82.2
		3	80.27	
		6	81.6	
		9	82.2	
		12	83.87	
2	R2	1	93.6	93.07
		3	92.4	
		6	91.87	
		9	93.33	
		12	94.13	
3	R3	1	82.07	81.49
		3	80.6	
		6	80.33	
		9	85.6	
		12	78.87	

**Table 7. Color features in reduced feature set R2.**

Sl. No	Color feature	Feature identifier	Sl. No	Color feature	Feature identifier
1	Red Mean	F1	6	Blue Standard Deviation	F10
2	Red Standard Deviation	F2	7	Hue Mean	F13
3	Green Mean	F5	8	Hue Standard Deviation	F14
4	Green Standard Deviation	F6	9	Intensity Mean	F21
5	Blue Mean	F9	10	Intensity Standard Deviation	F22

**Table 8. Ageing period classification results of all the paddy varieties using reduced ten color features from set R2 (Performance Threshold → 30%).**

Sl. No	Paddy variety	Classification accuracy per ageing period (%)				
		1 Month	3 Months	6 Months	9 Months	12 Months
1	Abhilasha	92	92	94	94	96
2	Bhagyajyothi	94	96	90	96	94
3	Budda	96	90	86	94	92
4	Intan	90	92	90	94	94
5	Jaya	94	90	92	88	98
6	Jayashree	90	92	90	94	90
7	Mugad Dodiga	96	92	96	94	94
8	Mugad Sughand	94	94	92	92	96

9	Mugad 101	94	96	90	94	96
10	Mugad Siri	94	90	94	92	98
11	PSB 68	96	90	96	94	94
12	Rajkaima	92	94	88	92	86
13	Redjyothi	96	92	92	94	96
14	Thousand Ten	92	92	94	94	92
15	Thousand One	94	94	94	94	96
<b>Average Ageing Period Classification Accuracy per ageing period (%)</b>		93.60	92.40	91.87	93.33	94.13

**Table 9. The confusion matrix for the classification of ageing periods using ten reduced color features.**

Sl. No	Paddy variety	Actual ageing periods in months	Predicted ageing periods in months					Total number of test images per ageing period
			1	3	6	9	12	
1	Abhilasha	1	46	3	1	0	0	50
		3	2	46	2	0	0	50
		6	0	1	48	1	0	50
		9	0	0	0	48	2	50
		12	0	1	0	1	48	50
2	Bhagyajyothi	1	47	2	1	0	0	50
		3	0	48	1	1	0	50
		6	1	2	45	2	0	50
		9	0	0	1	47	2	50
		12	0	1	2	1	46	50
3	Budda	1	48	2	0	0	0	50
		3	1	45	3	1	0	50
		6	1	2	43	3	1	50
		9	0	0	1	47	2	50
		12	0	1	1	2	46	50
4	Intan	1	47	2	1	0	0	50
		3	0	48	1	1	0	50
		6	1	2	45	2	0	50
		9	0	0	1	47	2	50
		12	0	1	2	1	46	50
5	Jaya	1	47	1	1	1	0	50
		3	3	45	1	1	0	50
		6	1	1	46	2	0	50
		9	0	0	3	44	3	50
		12	0	0	0	1	49	50
6	Jayashree	1	45	2	2	1	0	50
		3	2	46	1	1	0	50
		6	1	2	45	2	0	50
		9	0	0	1	47	2	50
		12	0	1	2	2	45	50
7	Mugad Dodiga	1	48	2	0	0	0	50
		3	2	46	1	1	0	50
		6	0	1	48	1	0	50
		9	0	0	1	47	2	50
		12	0	0	2	1	47	50

**Table 9. Confusion matrix for the classification of ageing periods using ten reduced color features (Continued...).**

Sl. No	Paddy variety	Actual ageing periods in months	Predicted ageing periods in months					Total number of test images per ageing period
			1	3	6	9	12	
8	Mugad Sughand	1	47	3	0	0	0	50
		3	2	47	1	0	0	50
		6	1	2	46	1	0	50
		9	0	0	2	46	2	50
		12	0	0	1	1	48	50
9	Mugad 101	1	47	2	1	0	0	50
		3	0	48	1	1	0	50
		6	1	2	45	2	0	50
		9	0	0	1	47	2	50
		12	0	1	2	1	46	50
10	Mugad Siri	1	47	2	1	0	0	50
		3	3	45	2	0	0	50
		6	0	2	47	1	0	50
		9	0	0	2	46	2	50
		12	0	0	0	1	49	50
11	PSB 68	1	48	1	1	0	0	50
		3	1	45	2	2	0	50
		6	0	2	48	0	0	50
		9	0	0	2	47	1	50
		12	0	0	2	1	47	50
12	Rajkaima	1	46	2	2	0	0	50
		3	0	47	2	1	0	50
		6	1	3	44	2	0	50
		9	0	0	2	46	2	50
		12	0	0	4	3	43	50
13	Redjyothi	1	48	2	0	0	0	50
		3	0	46	3	1	0	50
		6	0	3	46	1	0	50
		9	0	0	2	47	1	50
		12	0	0	1	1	48	50
14	Thousand Ten	1	46	2	1	0	0	49
		3	2	46	1	1	0	50
		6	0	2	47	1	0	50
		9	0	0	1	47	2	50
		12	0	0	1	1	48	50
15	Thousand One	1	47	3	0	0	0	50
		3	0	47	2	1	0	50
		6	0	2	47	1	0	50
		9	0	0	3	47	0	50
		12	0	0	1	1	48	50

**Table 10. Comparison of proposed work with the reported work.**

Author	Number of varieties considered	Ageing periods	Data set size	Features	Feature reduction method	Reduced feature set size	Classifier	Mean classification accuracy
Xiaoli Li et. al. (2008)	4	1, 2, 3 and 4 years	210 images	Wavelet features	Principal Component Analysis	8	ANN with Backpropagation	97.5
Proposed Work	15	1, 3, 6, 9 and 12 months	7500 images	Color features	Performance based feature reduction	10	ANN with Backpropagation	93.07