An edge texture features based methodology for bulk paddy variety recognition

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Abstract: The paper presents a method for recognition of paddy varieties from their bulk grain sample edge images based on Haralick texture features extracted from grey level co-occurrence matrices. The edge images were obtained using Canny and maximum gradient edge detection methods. The average paddy variety recognition performances of the two categories of edge images were evaluated and compared. A feature set of thirteen texture features was considered and the feature set was reduced based on contribution of each feature to the paddy variety recognition accuracy. The average paddy variety recognition accuracy of 87.80% was obtained for the reduced eight texture features extracted from maximum gradient edge images. The work is useful in developing a machine vision system for agriculture produce market and developing multimedia applications in agriculture sciences.

Keywords: paddy, canny, sobel, texture features, feature extraction, ANN, pattern recognition

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1 Introduction

India is an agriculture based country which decides its economy. Agriculture sector contributes around 26% of the gross domestic product (GDP). Paddy, jowar, wheat, sugarcane, maize are few major crops in different parts of India. Paddy is one of the most important universal cereal grain crops and it is grown in all the continents except Antarctica. India is the second largest producer of wheat and paddy. India and China are competing to establish the world record on rice yields. Its cultivation is of immense importance to food security of Asia, where more than 90% of the global rice is produced and consumed.

Human beings recognize the paddy varieties during quality evaluation and cultivation. The grain quality, yield, resistance to pests and diseases, tolerance to environmental stresses, farm input requirement, the production of rice, rice flakes and puffed rice and pricing, all these depend upon the variety. At present paddy grain handling operation is carried out manually (also referred to as visual inspection) by the trained personnel and is considered as time consuming and moreover subjective. These shortcomings of manual approach demand for the development of a machine vision system to automatically carry out recognition of paddy variety. This automation would benefit the potential farmers in getting their right price and right variety for cultivation. In order to know the state-of-the-art in automation of such activities in the field of agriculture, we have carried out a survey and the gist of papers given under is divided into two broad categories, one paddy related and the other allied.

Mousavi et al. (2014) presented an algorithm to classify five different varieties of rice from unshelled singleton kernel using the color and texture features. The method used a feed-forward neural network classifier for recognition of rice varieties and obtained 96.67% accuracy. Golpour et al. (2014) proposed an image processing

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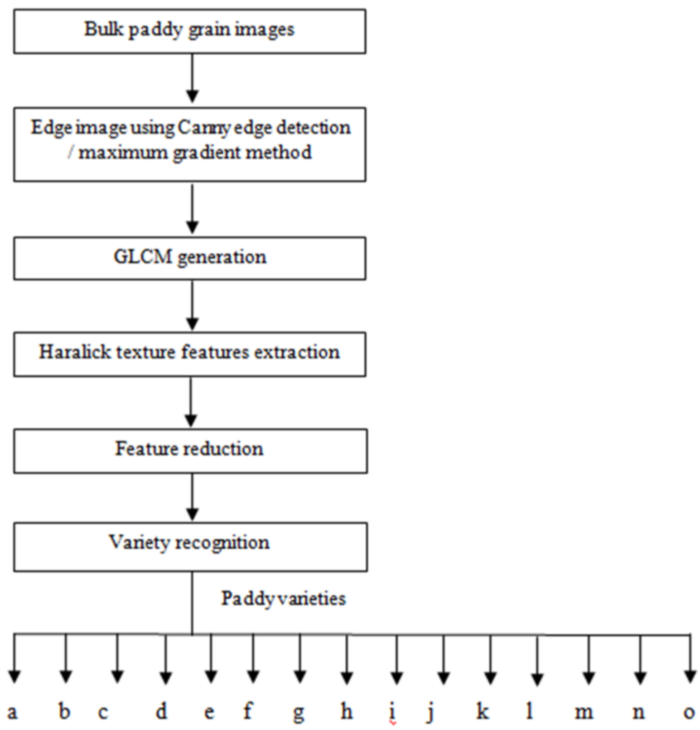
algorithm for classification of bulk paddy, brown and white variety using 36 color features in RGB, HSI and HSV color spaces. The algorithm adopted back propagation neural network for classification and obtained a mean classification accuracy of 96.66% with 13 color features. Pazoki et al. (2014) proposed a methodology for the classification of five paddy grain varieties using 24 color features, 11 morphological features and four shape features. The features extracted from color images of singleton grains of paddy gave classification accuracies of 99.46% and 99.73% for multi-layer perceptron (MLP) and neuro-fuzzy classifiers respectively. Archana et al. (2014) proposed an algorithm to classify four paddy varieties from shape and texture features using artificial neural network. The algorithm gave accuracies of 82.61%, 88.00%, and 87.27% for texture, shape and texture and shape features respectively. The algorithm used singleton paddy grain images. Mousavi et al. (2012) presented image processing techniques to identify five different classes of unshelled rice varieties using ensemble classifier. The forty-one morphological features used to train ANN classifier gave 99.86% recognition accuracy. Pourreza et al. (2012) applied machine vision techniques for the classification of wheat varieties using one hundred and thirty one texture features. The features included were GLCM (gray level co-occurrence matrix), GLRM (gray level run-length matrix), LBP (local binary patterns), LSP (local similarity patterns) and LSN (local similarity numbers). The deployed LDA (linear discriminate analysis) classifier gave an average classification accuracy of 98.15%. The results revealed that LSP, LSN and LBP features had significant influence on classification accuracy. Guzman et al. (2008) proposed a machine vision system based on neural networks for automatic identification of five paddy varieties of Philippines based on morphological features. The method gave a classification accuracy of 70%.

Savakar (2010) illustrated an algorithm for recognition and classification of similar looking grain images using back propagation artificial neural network. The method gave accuracy in the range 78%-84% for individual color and texture features and in the range 85%-90% for combined color and texture features. Anami et al. (2009) presented a methodology to identify the different grain types from image samples of tray containing multiple grains using color and textural features. A back propagation neural network was used for identification of bulk food grains using eighteen color and texture features. Five different types of grains namely, alasandi, green gram, metagi, red gram and wheat were tested and identification accuracies observed in this work were 94% and 80% for wheat and alasandi. Anami et al. (2005) developed a Neural network approach for classification of single grain kernels of different grains like wheat, maize, groundnut, redgram, greengram and blackgram based on color, area covered, height and width. The minimum and maximum classification accuracies reported were 80% and 90% respectively. Anami et al. (2009) presented different methodologies devised for recognition and classification of images of agricultural/horticultural produce based on BPNN using color, texture and morphological features with 87.5% accuracy. Huang et al. (2004) proposed an identification method based on Bayes' decision theory to classify rice variety from individual grain samples using color and shape features with 88.3% accuracy. Visen et al. (2004) proposed combined color and texture features based methodology to identify grain type from color images of bulk grains using back propagation neural network. A feature set consisting of 154 features was reduced to 20. Classification accuracies of over 98% were obtained for five grain types, namely barley, oats, rye, wheat, and durum wheat for combined ten color features and ten texture features, Paliwal et al. (2004) proposed a robust algorithm for classifying images of bulk samples of barley, wheat, oats, and rye using a four layer back propagation neural network and obtained classification accuracy of 99% using combined color and texture features. Shearer and Holmes (1990) proposed a method for identifying plants based on color texture characterization of canopy sections. Color co-occurrence matrices were derived from images, one for each color attribute: intensity, saturation, and hue giving 11 texture features. The LDA with 33 color texture features were used to identify plants. Overall classification accuracy of 91% was obtained.

From the literature survey, it is observed that there is some amount of research carried related to recognition and classification of paddy grains and rice kernels. The published work has mainly focused on classification of paddy grains in singleton and non-touching grains. The number of varieties is small. The morphological, color, texture and shape features are employed in the works. The size of the feature set adopted is large and amounts to increased computational overhead during classification of bulk paddy grains. Further, limited work is noticed on variety identification from bulk samples of paddy grains. This is the motivation for the present work, with an aim to devise a smaller feature set, based on edge texture features for variety recognition from bulk paddy grain sample images.

2 Proposed methods

The proposed method consists of four stages, namely, image acquisition, edge detection, feature extraction, feature selection and paddy variety recognition as shown in Figure 1. The bulk sample edge images of fifteen paddy grain varieties and Haralick texture features are considered. A multilayer feed-forward artificial neural network is used as recognizer of paddy varieties.



	Paddy Varieties
a	Abhilasha
b	Bhagyajyothi
c	Budda
d	Intan
e	Jaya
f	Jayashree
g	Mugad dodiga
h	Mugad sughand
i	Mugad 101
j	Mugad siri
k	PSB 68
l	Rajkaima
m	Redjyothi
n	Thousand ten
o	Thousand one

Figure 1 Block diagram of the proposed methods

2.1 Image acquisition

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 paddy varieties are obtained from Agricultural Research Station, Mugad, Dharwad. These varieties are grown in different parts of Karnataka, India. The varieties considered in the work include Abhilasha, Bhagyajyothi, Budda, Intan, Jaya, Jayashree, Mugad dodiga, Mugad sughand, Mugad 101, Mugad siri, PSB 68, Rajkaima, Redjyothi, Thousand one and Thousand ten. The images of paddy varieties are shown in Figure 2.

(a) Abhilasha (b) Bhagyajyothi (c) Budda (d) Intan (e) Jaya (f) Jayashree
(g) Mugad dodiga (h) Mugad sughand (i) Mugad 101 (j) Mugad siri
(k) PSB 68 (l) Rajakaima (m) Redjyothi (n) Thousand one (o) Thousand ten

Figure 2 Images of paddy varieties

A total 3000 images, considering 200 images from each type of 15 paddy varieties are acquired under standard lighting conditions using color camera PENTAX MX-1, USA, having resolution of 14 mega pixels. In order to provide a stable support and easy vertical movement, the camera is mounted on a tripod stand as shown in Figure 3. The images are taken keeping approximately the object distance of 0.5 m. The acquired images of size 1920 pixels × 1080 pixels are resized to 400 pixels × 400 pixels for reasons of reduction in computational overhead and storage requirements.

Figure 3 Image acquisition setup

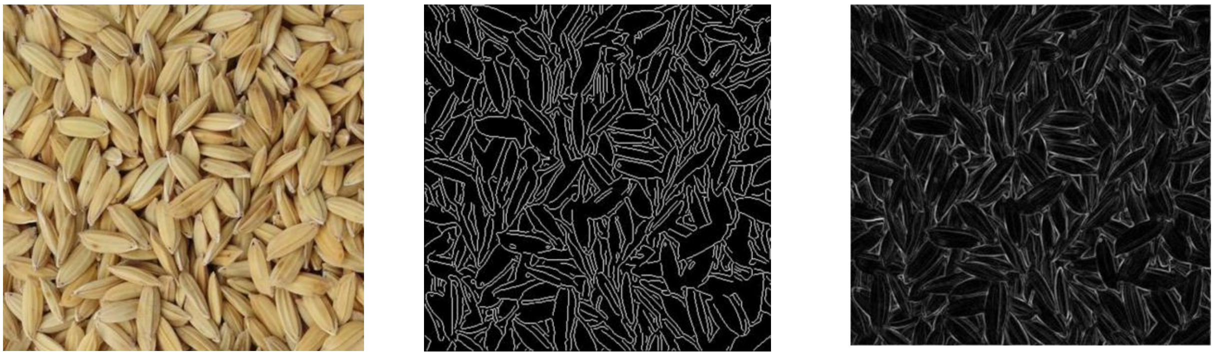
2.2 Edge detection

The edges in bulk sample of paddy grain images are considered to be the most important image attributes that exhibit different texture properties as shown in Figure 4 and provide valuable information for paddy variety identification. This is the reason for adopting texture analysis of edge images for paddy variety identification from their bulk samples. Two standard edge detection methods namely, Canny and maximum gradient method are used to obtain edge images from RGB bulk paddy grain image samples. The Canny edge detection method basically finds edges where the grayscale intensity of the image changes the most as shown in Figure 4b. These areas are found by determining gradients of the image. The maximum gradient method determines gradients at each pixel in the image by applying Sobel operator and returns edges at those points where the gradient of the image is the maximum. The maximum gradient edge image is shown in Figure 4c. It is clear from Figure 4b and Figure 4c that the maximum gradient edge detection method is able to detect more edges than the Canny edge detection method.

2.3 Feature extraction

From the edge images obtained using Canny and maximum gradient edge detection methods, thirteen Haralick texture features are extracted using gray level co-occurrence matrix method (GLCM) and the texture features are listed in Table 1. The GLCM $P_{\varphi, d}$ (i, j) represents a matrix of relative frequencies describing how frequency pair of gray levels (i, j) appear in the window separated by a given distance d = (d_x, dy) at an angle 'φ'. Gray level co-occurrence matrices (GLCMs) method counts how often pairs of gray level of pixels separated by certain distance and oriented in a certain direction, while scanning the image from left-to-right and top-to-bottom. In the present work, a distance of 1 (d=1) when 'φ' is 0° or 90° and √2 (d= √2) when 'φ' is 45° or 135° has been considered. The procedure of computing the co-occurrence matrix is given in the Algorithm 1.

Algorithm 1: Computation of co-occurrence matrix $P_{\varphi, d}(i, j)$ from the image $P(i, j)$



(a) (b) (c)

(a) Original RGB image (b) Canny edge image (c) Maximum gradient edge image

Figure 4 Bulk paddy images.

Input: Color (RGB) image.

Output: Co-occurrence matrix $P_{\varphi, d}(i, j)$ for $d=1$ in the direction *'φ'*.

Start

Step 1: Convert input color image to gray level image $P(i, j)$

Step 2: Assign $P_{\varphi, d}(i, j)$ =0 for all i, j Є [0, L], where 'L' is the maximum gray level

Step 3: For all pixels *(i1, j1)* in the image, determine *(i2, j2)*, which is at distance *'d'* in direction *'φ'* of (0^0, 45^0, 90^0, and 135^0) and compute $P(i, j) \mid p(i1, j1), p(i2, j2)\mid = P_{\varphi, d} \mid p(i1, j1), p(i2, j2)\mid + 1$

Step 4: Compute $P_{\varphi, d} = \frac{1}{4}(p_{0, d} + p_{45, d} + p_{90, d} + p_{135, d})$

Stop.

In order to define Haralick features, GLCM is normalized as given in the Equation (1).

$$P(i,j) = \frac{p(i,j,1,0)}{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p(i,j,1,0)} \quad (1)$$

Where,

$$P_x(i) = \sum_{j=0}^{N_g-1} P_{\varphi,d}(i,j) \quad (2)$$

$$P_y(j) = \sum_{i=0}^{N_g-1} P_{\varphi,d}(i,j) \quad (3)$$

Where, $P_x(i)$ and $P_y(i)$ are marginal probability matrices, $P(i, j)$ is the image attribute matrix, $p(i, j, 1, 0)$ represents the intensity co-occurrence matrix, N_g is total number of intensity levels.

The Haralick features are defined as follows.

The angular moment (F1) or energy measures image uniformity.

$$F1 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} [[P(i,j)]]^2 \quad (4)$$

Contrast (F2) measures intensity or gray level variations between the pixel and its neighborhood.

$$F2 = \sum_{i=0}^{N_g-1} k^2 \sum_{|i-j|}^{N_g-1} P(i,j) \quad (5)$$

Where,

k=0, 1, 2……., 2 (N_g - 1)

Correlation (F3) measures intensity linear dependence of gray level values to its neighborhood. Here, μ_x and μ_y are the means and σ_x and σ_y are the standard deviations of P_x and P_y respectively.

$$F3 = \frac{1}{\sigma_x \sigma_y}\left(\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} i\, j\, P(i,j) - \mu_x\ \mu_y\right) \quad (6)$$

The sum of squares (F_4) is defined by

$$F4 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i - \mu_f)^2 P(i,j) \quad (7)$$

Where, μ_f is the mean gray level of the image.

Inverse difference moment (F5) is generally called homogeneity that measures local homogeneity of the image.

$$F5 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i - j)^2 + P(i,j) \quad (8)$$

The sum average feature (F6) is defined by

$$F6 = \sum_{k=0}^{2(N_g-1)} kP_{x+y}(k) \quad (9)$$

The sum variance feature (F7) is defined by

$$F7 = \sum_{k=0}^{2(N_g-1)} (k - F6)^2 P_{x+y}(k) \quad (10)$$

The sum and difference entropies (F8 and F9) are defined by

$$F8 = \sum_{k=0}^{2(N_g-1)} P_{x+y}(k) \ln P_{x+y}(k) \quad (11)$$

$$F9 = \sum_{k=0}^{N_g-1} P_{x-y}(k) \ln P_{x-y}(k) \quad (12)$$

The entropy feature (F10) measures randomness of intensity in the image defined by

$$F10 = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P(i,j) \ln P(i,j) \quad (13)$$

The difference variance (F11) is defined by

$$F11 = Variance\ of\ P_{x-y} \quad (14)$$

The information measures of correlation (F12 and F13) are defined by

$$F12 = (HXY - HXY1)/(max(HX, HY)) \quad (15)$$

$$F13 = \left[1 - exp^{-2(HXY2 - HXY)}\right]^{\frac{1}{2}} \quad (16)$$

Where,

$$HX = -\sum_{I=0}^{N_g-1} P_x(i) \ln P_x(i) \quad (17)$$

$$HXY1 = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P(i,j) \ln\left[P_x(i)P_y(j)\right] \quad (18)$$

$$HXY2 = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P_x(i)P_y(j) \ln\left[P_x(i)P_y(j)\right] \quad (19)$$

The procedure used in obtaining the texture features based on co-occurrence matrix is given in the Algorithm 2 and the Equations (4) to (16) are being used in the algorithm to extract Haralick texture features. The features are listed in Table 1.

Algorithm 2: GLCM texture feature extraction

Input: Color (RGB) image.

Output: Texture features.

Description: $P_{\varphi, d}(i, j)$ means GLCM matrices in the direction $\varphi = 0^0, 45^0, 90^0$, and 135^0 and *'d'* is the distance.

Start

Step 1: Compute the co-occurrence matrix which is independent of direction using

Algorithm 1

Step 2: Calculate co-occurrence texture features using Equations (4) through (16)

Stop.

Table 1 Haralick texture features

Sl. No	Feature	Feature identifier
1	Energy	F1
2	Contrast	F2
3	Correlation	F3
4	Variance	F4
5	Inverse difference moment	F5
6	Sum average	F6
7	Sum variance	F7
8	Sum entropy	F8
9	Difference entropy	F9
10	Entropy	F10
11	Difference variance	F11
12	Information measures of correlation 1	F12
13	Information measures of correlation 2	F13

2.3.1 Canny edge texture features extraction

Thirteen Haralick texture features are extracted from the Canny edge images of all the fifteen paddy varieties and the feature values are given in Table 2. The graphical representation of the texture feature values with respect to different paddy varieties are shown in Figure 5.

Table 2 Texture feature values extracted from bulk paddy grain Canny edge images

Sl. No	Paddy variety	Haralick texture features												
		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
1	Abhilasha	0.6523	0.1739	0.1484	0.1739	0.913	0.2309	0.2345	0.8428	0.6654	1.0167	0.1434	-0.03	0.1573
2	Bhagyajyothi	0.641	0.181	0.1445	0.181	0.9095	0.2404	0.242	0.859	0.6783	1.04	0.1475	-0.0374	0.1505
3	Budda	0.6555	0.1723	0.1495	0.1723	0.9138	0.2288	0.2328	0.833	0.6591	1.0054	0.1419	-0.04	0.1536
4	Intan	0.648	0.1766	0.147	0.1766	0.9117	0.2345	0.2374	0.8494	0.6706	1.026	0.145	-0.0318	0.1549
5	Jaya	0.6617	0.1686	0.152	0.1686	0.9157	0.2239	0.229	0.8225	0.651	0.9911	0.1395	-0.04	0.1565
6	Jayashree	0.5905	0.213	0.1231	0.213	0.8935	0.2829	0.2727	0.945	0.7427	1.158	0.1666	-0.0302	0.139
7	Mugad dodiga	0.6607	0.1691	0.1513	0.1691	0.9155	0.2244	0.2293	0.8265	0.6535	0.9956	0.1401	-0.0341	0.1582
8	Mugad sughand	0.6348	0.1854	0.141	0.1854	0.9073	0.2461	0.2462	0.8625	0.6833	1.0479	0.1494	-0.0523	0.1598
9	Mugad 101	0.6497	0.1755	0.1475	0.1755	0.9122	0.233	0.2362	0.8469	0.6685	1.0224	0.1444	-0.031	0.1559
10	Mugad siri	0.6298	0.1881	0.1391	0.1881	0.906	0.2496	0.2488	0.8767	0.6926	1.0648	0.1517	-0.039	0.1452
11	PSB68	0.6548	0.173	0.1491	0.173	0.9135	0.2297	0.2336	0.8301	0.6581	1.0031	0.1419	-0.0495	0.1563
12	Rajkaima	0.62	0.1936	0.136	0.1936	0.9032	0.2572	0.2545	0.8999	0.7078	1.0935	0.1559	-0.0244	0.1475
13	Redjyothi	0.6484	0.1767	0.1466	0.1767	0.9117	0.2345	0.2372	0.8453	0.6684	1.022	0.1446	-0.0391	0.158
14	Thousand one	0.6709	0.1629	0.156	0.1629	0.9185	0.2165	0.2231	0.8083	0.6393	0.9712	0.136	-0.0362	0.1619
15	Thousand ten	0.6443	0.179	0.1456	0.179	0.9105	0.2378	0.24	0.8535	0.6743	1.0325	0.1462	-0.0373	0.152

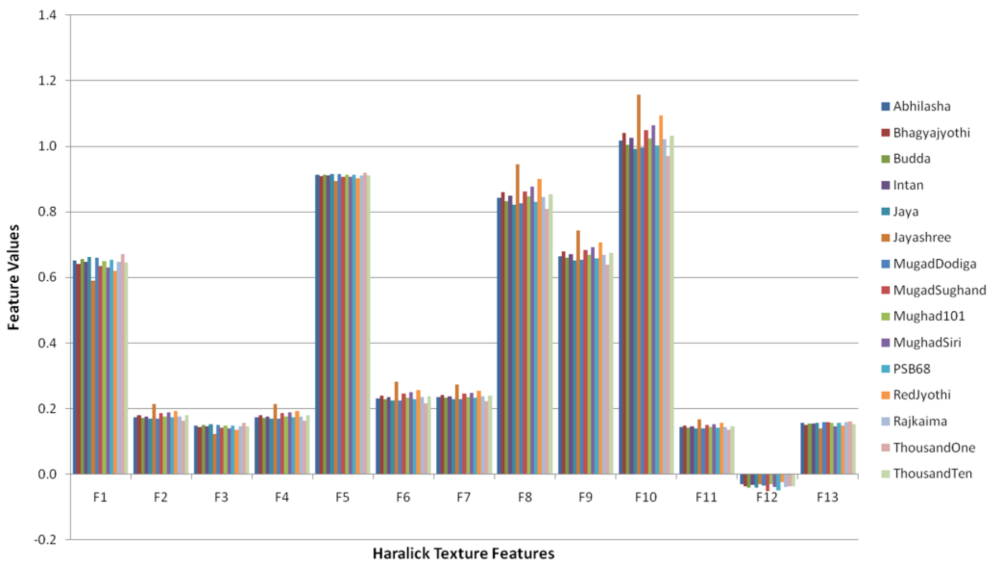


Figure 5 Graphical representation of texture feature values of bulk paddy grain Canny edge images

2.3.2 Gradient edge texture features extraction

Thirteen Haralick texture features are extracted from the gradient edge images of all the fifteen paddy varieties and the feature values are given in Table 3. The graphical representation of the texture feature values with respect to different paddy varieties are shown in Figure 6.

Table 3 Texture feature values extracted from bulk paddy grain gradient edge images

Sl. No	Paddy variety	Haralick texture features												
		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
1	Abhilasha	0.7252	0.7301	0.9193	0.9399	0.1666	0.2818	0.5718	0.8045	0.4681	0.1248	0.1516	-0.0011	0.0873
2	Bhagyajyothi	0.4681	0.6674	0.9112	0.9977	0.1550	0.2981	0.5955	0.8079	0.4756	0.1260	0.1761	-0.0009	0.0830
3	Budda	0.5017	0.7162	0.9424	0.8701	0.1733	0.2617	0.7242	0.8305	0.4566	0.1268	0.1385	-0.0011	0.0869
4	Intan	0.5994	0.6984	0.9206	1.0994	0.1417	0.2645	0.7659	0.8343	0.4905	0.1303	0.1940	-0.0011	0.0861
5	Jaya	0.7742	0.6924	0.9277	0.8460	0.1948	0.2974	0.5688	0.7967	0.4513	0.1219	0.1416	-0.0011	0.0869
6	Jayashree	0.2884	0.6215	0.8912	1.1774	0.1328	0.2963	0.6100	0.8182	0.5003	0.1297	0.2111	-0.0007	0.0789
7	Mugad dodiga	0.5816	0.7149	0.9397	0.9040	0.1696	0.2609	0.7398	0.8332	0.4618	0.1275	0.1475	-0.0011	0.0872
8	Mugad sughand	0.5572	0.7548	0.9497	0.8149	0.1853	0.2637	0.7314	0.8295	0.4476	0.1257	0.1214	-0.0013	0.0908
9	Mugad 101	0.5394	0.6772	0.9231	0.9552	0.1616	0.2745	0.6194	0.8139	0.4702	0.1262	0.1551	-0.0010	0.0841
10	Mugad siri	0.3699	0.6849	0.9274	1.0307	0.1513	0.2685	0.7507	0.8307	0.4812	0.1291	0.1759	-0.0010	0.0855
11	PSB68	0.7551	0.7387	0.9421	0.7666	0.2086	0.2876	0.5951	0.8013	0.4381	0.1211	0.1186	-0.0012	0.0892
12	Rajkaima	0.3812	0.7022	0.9195	0.9758	0.1658	0.2849	0.6396	0.8160	0.4711	0.1263	0.1668	-0.0009	0.0840
13	Redjyothi	0.5461	0.6897	0.8778	1.3231	0.1101	0.2874	0.6615	0.8223	0.5173	0.1320	0.2545	-0.0011	0.0863
14	Thousand one	0.5567	0.6932	0.9180	0.9342	0.1777	0.3001	0.5842	0.7995	0.4657	0.1236	0.1618	-0.0011	0.0857
15	Thousand ten	0.5200	0.6920	0.9271	0.9356	0.1706	0.2796	0.6625	0.8194	0.4653	0.1262	0.1554	-0.0010	0.0855

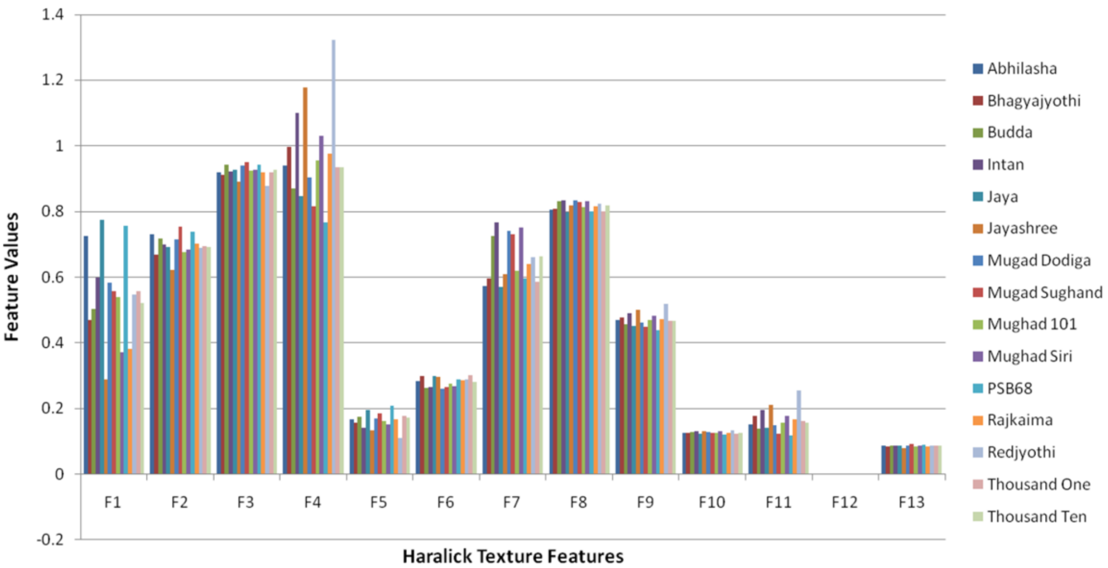


Figure 6 Graphical representation of texture feature values of bulk paddy grain gradient edge images

2.4 Feature selection

In order to reduce the computational overhead, the feature set is reduced. The useful features that contribute to the recognition process are selected by testing each individual texture feature for paddy variety recognition and performance feature selection is carried out. The procedure for selecting significant features is given in Algorithm 3.

Algorithm 3: Recognition performance based texture feature selection.

Input: Extracted texture features along with their respective average recognition accuracies (P_{ARA}).

Output: Reduced feature sets with selected features.

Start

Step 1: Find out minimum and maximum average recognition accuracies in all the texture features.

$X = MINIMUM(P_{ARA})$ // Minimum average recognition accuracy in all the texture features

$Y = MAXIMUM(P_{ARA})$ // Maximum average recognition accuracy in all the texture features

Step 2: Compute recognition accuracy threshold (RAT) value.

RAT = (X + Y)/2

Step 3: Compare the average recognition accuracies of all the features with *RAT*.

Construct reduced feature set by selecting the texture features whose average recognition accuracies are equal to or greater than the *RAT* value.

Step 4: Compare, if *RAT* <= *Y*, then *X* = *RAT* and go to Step 2 else return the reduced feature sets.

End

2.5 Recognition of paddy varieties

A multilayer feed-forward neural network is considered for paddy variety recognition. The number of neurons in the input layer is set to the number of appropriate texture features selected as input and the output layer is set to 15. Levenberg-Marquardt (LM) back propagation algorithm is used for the training. The termination error (TE) is set to 0.01, learning rate (η) is set to 0.05 and momentum coefficient (μ) 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 network is trained. Once the training is complete, the test data for each of the paddy variety is tested. The overall recognition process is given in Algorithm 4.

Algorithm 4: Overall recognition of paddy varieties from bulk grain sample images using color texture features.

Input: Bulk paddy sample images of different varieties.

Output: Recognized paddy variety

Start

Step 1: Convert color (RGB) input images into (Canny/Gradient) edge images.

Step 2: Compute co-occurrence matrix (GLCM) for the edge images using Algorithm 1.

Step 3: Extract texture features of the edge images using Algorithm 2.

Step 4: Perform feature selection using Algorithm 3

Step 5: Train artificial neural network (ANN) with the selected texture feature set obtained in Step 4.

Step 6: Accept test image and extract the selected texture features using Algorithm 3.

Step 7: Recognize the image containing bulk paddy sample using ANN classifier. Repeat the steps 6 and 7 for all the test images.

End

3 Results and discussion

The software tool MATLAB 7.11.0 is used to implement the devised algorithms. A total of 3000 image samples, 200 images of each varietal type are considered. Out of these image samples 1500 images (100 images of each paddy variety) are used for training and 1500 images (100 images of each paddy variety) are used for testing. The percentage of recognition accuracy as the ratio of total number of correctly recognized test image samples to the total number of test image samples is given by the Equation (20). The average recognition accuracy (PARA) is calculated as the ratio of sum of recognition accuracies of all the paddy varieties to the total number of paddy varieties considered and is given by the Equation (21).

$$P_A = \frac{T_C}{T_T} \times 100\ \% \qquad (20)$$

Where, P_A is the percentage of recognition accuracy (%); T_C is the total number of correctly recognized images; and T_T is the total number of test images.

$$P_{ARA} = \frac{\sum_{i=1}^{T_N} P_{Ai}}{T_N} \qquad (21)$$

Where, P_{ARA} is Average recognition accuracy (%); i is the variety order number; P_{Ai} percentage of recognition accuracy of i^{th} variety; and T_N is the total number of the paddy varieties.

3.1 Variety recognition using canny edge texture features

The training and testing processes are carried out using texture features extracted from the Canny edge images of bulk sample of 15 paddy varieties. Initially, 13 texture features are considered for the paddy recognition process and obtained average variety recognition accuracy of 70.20% across 15 paddy varieties as given in Table 4.

Table 4 Paddy variety recognition using edge texture features

Sl. No	Paddy varieties	Texture features	
		Canny edge texture features	Gradient edge texture features
1	Abhilasha	67	88
2	Bhagyajyothi	69	96
3	Budda	73	92
4	Intan	69	81
5	Jaya	64	75
6	Jayashree	71	69
7	Mugad dodiga	67	71
8	Mugad sughand	77	73
9	Mugad 101	67	69
10	Mugad siri	80	89
11	PSB 68	65	82
12	Rajkaima	73	78
13	Redjyothi	70	90
14	Thousand one	72	91
15	Thousand ten	69	87
	P_{ARA}, %	**70.20**	**82.07**

3.2 Variety recognition using gradient edge texture features

The training and testing processes are carried out using texture features extracted from the gradient edge images of bulk sample of 15 paddy varieties. Initially, 13 texture features are considered for the paddy recognition process and obtained average variety recognition accuracy of 82.07% across 15 paddy varieties as given in Table 4. It is observed from the Table 4 that the gradient edge texture features give better average recognition accuracy over canny edge texture features. So we have adopted gradient edge texture features for paddy variety identification.

In order to improve the recognition accuracy of gradient edge texture features, the performance based feature selection operation is carried out using Algorithm 3. The recognition accuracies of all the individual gradient edge texture features are evaluated as input to the algorithm and the recognition accuracies are given in Table 5. The reduce feature sets and their sizes obtained using the algorithm are given in Table 6. The reduced feature sets are trained and tested using ANN and the obtained results are given in Table 7. From Table 7, the highest average recognition accuracy of 87.80% is obtained for the reduced feature set with size 11 and the paddy variety Abhilasha gives the highest recognition accuracy of 96% and lowest is obtained for the paddy variety PSB 68. The recognition performances of all the reduced gradient edge texture feature sets are graphically shown in Figure 7.

Table 5 Paddy variety recognition performance of individual gradient edge texture feature

Sl. No	Paddy varieties	Gradient edge texture features												
		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
1	Abhilasha	53	26	31	45	41	33	42	49	45	66	46	1	16
2	Bhagyajyothi	57	30	33	49	45	37	43	57	51	55	37	6	12
3	Budda	50	23	29	55	41	41	36	48	58	49	33	7	21
4	Intan	48	36	32	52	47	28	47	50	51	67	36	3	28
5	Jaya	47	41	36	53	51	31	42	54	67	77	42	11	23
6	Jayashree	45	24	24	51	43	33	37	58	62	47	36	3	19
7	Mugad dodiga	47	28	20	51	46	36	33	56	63	56	33	21	22
8	Mugad sughand	46	31	38	49	44	44	38	52	55	55	31	1	26
9	Mugad 101	51	33	41	38	46	35	31	57	49	49	26	5	24
10	Mugad siri	49	37	22	43	51	40	45	54	52	53	29	10	29
11	PSB 68	52	40	37	40	49	31	42	49	40	47	36	6	16
12	Rajkaima	49	28	37	47	46	30	38	54	44	45	41	2	19
13	Redjyothi	52	38	32	39	49	27	32	50	62	58	25	16	31
14	Thousand ten	51	29	35	47	47	37	35	55	39	65	35	2	26
15	Thousand one	55	30	33	29	50	29	41	44	54	50	30	9	30
	P_{ARA}, %	**50.13**	**31.60**	**32.00**	**45.87**	**46.40**	**34.13**	**38.80**	**52.47**	**52.80**	**55.93**	**34.40**	**6.87**	**22.80**

Table 6 Reduced feature sets obtained from Algorithm 3

Y (Maximum P_{ARA})	X (Minimum P_{ARA})	Recognition accuracy threshold (RAT)	Reduced feature sets	Reduced feature set size
55.93	6.87	31.40	F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, F11	11
55.93	31.40	43.67	F1, F4, F5, F8, F9, F10	6
55.93	43.67	49.80	F1, F8, F9, F10	4
55.93	49.80	52.87	F9, F10	2

Table 7 Paddy variety recognition performance of reduced gradient edge texture features

Sl. No	Paddy variety	Reduce feature set sizes				
		2	4	6	11	13
1	Abhilasha	54	65	68	96	88
2	Bhagyajyothi	59	72	84	94	96
3	Budda	60	69	82	92	92
4	Intan	51	66	77	90	81
5	Jaya	66	77	75	89	75
6	Jayashree	59	73	69	85	69
7	Mugad dodiga	62	71	72	80	71
8	Mugad sughand	58	74	69	84	73
9	Mugad 101	63	68	72	83	69
10	Mugad siri	60	77	79	87	89
11	PSB 68	56	66	72	79	82
12	Rajkaima	61	71	68	90	78
13	Redjyothi	68	69	76	87	90
14	Thousand one	73	72	79	91	91
15	Thousand ten	62	57	77	90	87
	P_{ARA}, %	**60.80**	**69.80**	**74.60**	**87.80**	**82.07**

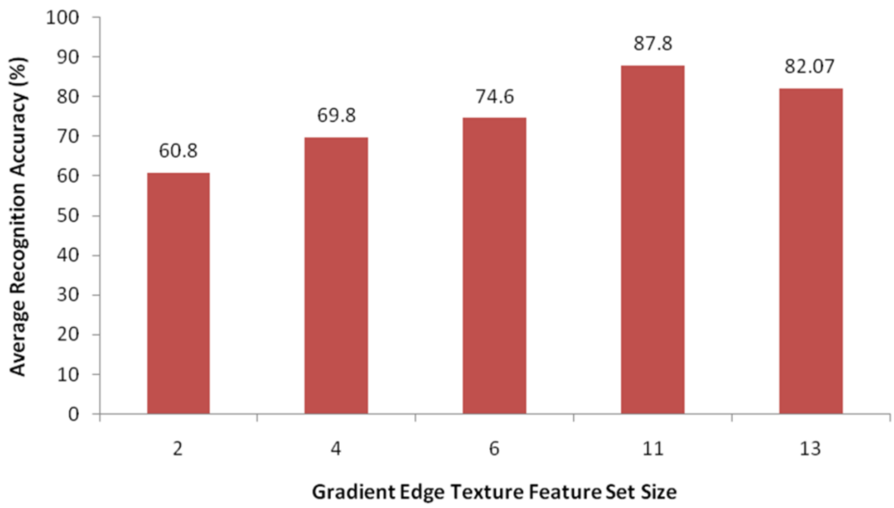


Figure 7 Graphical representation of gradient edge texture features performance in paddy variety recognition

The proposed method has considered fifteen paddy varieties, which is three times more than the reported work and the number of features considered is less than the features used in the reported work as depicted in Table 8.

Table 8 Comparison of proposed method with the literature

Literature	Number of paddy varieties	Sample type	Features	Accuracy (%)
(Guzman et al., 2008)	5	Singleton grain	13 morphological features	70.00
(Pazoki et al., 2014)	5	Singleton grain	24 color, 11 morphological, 4 shape features	99.73
(Golpur et al., 2014)	5	Bulk grains	13 color features	96.66
Proposed method	15	Bulk grains	11 gradient edge texture features	87.80

4 Conclusions

The Haralick texture features are used for the recognition of 15 paddy varieties from their bulk sample edge images. The Canny and maximum gradient edge detection methods are applied to obtain the edge images. The average recognition accuracy of 87.80% is obtained for reduced 11 texture features extracted from maximum gradient edge images which is better than the recognition result obtained using the texture features extracted from Canny edge images. The proposed method has considered number of varieties three times more and number of features used is nearly half than the reported work. The results are encouraging. The work finds application in developing a machine vision system for agriculture produce market and developing multimedia applications in agriculture sciences.

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