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Efficient technique for rice grain classification using back-propagation neural network and wavelet decomposition

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Abstract: This study describes the classification of four varieties of bulk rice grain images using back-propagation neural network (BPNN). Eighteen colour features, 27 texture features using grey-level co-occurrence matrix, 24 wavelet features and 45 combined features (combination of colour and texture) were extracted from the colour images of bulk rice grains. Classification was carried out on three different data set of images under different environmental conditions. It is seen that BPNN is able to classify faithfully the four varieties of rice grain even with a poor image quality. It is also found that classification based on reduced wavelet features outperform the classification using all other features (such as colour, texture features taken separately) for two data set of images with minimum resolution. The authors have further compared the proposed BPNN technique with other classifiers such as support vector machine, *k*-nearest neighbour and naive Bayes classifier on all the three data sets. It is found that the average classification accuracy of more than 96% was able to achieve using BPNN consistently on all different features for each data set.

1 Introduction

Digital image plays an important role in daily life as well as in the area of research and technology developments. A digital image is basically a two-dimensional representation of intensity levels of objects in the scene. Processing of digital image should be fast and cost effective. An image can effectively be stored and transmitted. However, the quality of digital image should not be degraded even if it is copied for several times [1]. Digital image processing refers to the manipulation of an image by means of a processor. Different elements of an image-processing system include image acquisition, image storage, image enhancement, segmentation, image description and display.

1.1 Background

One of the related fields of image processing is machine vision. The main goal of machine vision is to interpret the image and to extract its physical, geometrical or topological properties. The domain of machine vision encompasses illumination, image acquisition system, pixel processing as a part of the implementation of industrial projects. The application involving machine vision aims to inspect a large number of products in order to achieve desired quality controls. Inspection of agricultural product using machine vision has become an important research interest over the past few years. Unlike most of the other industrial products, the shape, size, colour and texture of the agricultural products are not governed by a unique mathematical function [2]. It has become a challenging task for the machine vision system to recognise and classify naturally varying appearance of biological entities like, cereal grain. Machine vision system has become an alternative to manual inspection of grain samples for kernel characteristic properties and the amount of foreign materials therein. Information of grain types and quality are required at several stages during grain handling operation. The present grain handling system of course, requires rapid access of grain types and quality through visual inspection. However, the processes involved are tedious and time consuming. The operator generally loses concentration after a few hours of working due to fatigue, eyesight and improper lighting. Thus, an automatic classifier can prevent human errors in the quality evaluation process, which has become an alternative to manual inspection of grain samples.

1.2 Related works

Research has been carried out to classify cereal grains based on grain kernel in a well setup and excellent imaging environment using morphological features like, area, perimeter, major axis, minor axis, elongation, compactness and so on in [2–7]. Characterisation model based on colour to extract the colour attributes from the input colour image and texture to extract information regarding arrangement of pixels in an image was also carried out in [8–11]. Research also has been carried out to classify grain kernel by combining all the above-mentioned features for improving classification accuracy [3, 8, 12, 13]. Most of the published works were based on identification of grain types by placing grain kernels in a non-touching fashion [2–7]. Such an identification process requires cumbersome setup and is difficult to implement on site. The system also requires a device to present kernel in a non- touching fashion. The pre-processing operation like, image segmentation, back-ground removal and object extraction are prerequisite and time-consuming operation. Many of the image pre-processing steps are not necessary if identification of grain is carried out using image of bulk samples [6, 9, 14–16]. Moreover, an image of a bulk sample does not contain individual objects in it. Hence, there is no need to pre-process the image for back-ground removal and object extraction. Classification of grain types using bulk grain image samples with colour and texture was carried out in [6, 9, 14–16]. Recent published works also include classification of colour images using support vector machine (SVM) and other statistical classifiers [17–19]. Classification of bulk grains by reducing the feature vector using stepdisc and feature's error was also carried out in [14, 20–22]. This paper describes classification of images of bulk rice samples using back-propagation neural network (BPNN) with lesser number of features without compromising the classification accuracy. The classification processes involve four stages – first stage deals with acquiring the image, the second stage deals with features extraction, the third stage focuses on classification and the last stage compares the classification accuracy of the proposed BPNN with other state-of-the-art techniques. The rest of the paper is organised as follows. Section 2 covers the materials and methods used in such a classification. Section 3 describes the image classification model. Section 4 discusses about the simulation results and its analysis. Section 5 concludes the paper.

Fig. 1 *Samples of rice colour images*

2 Materials and methods

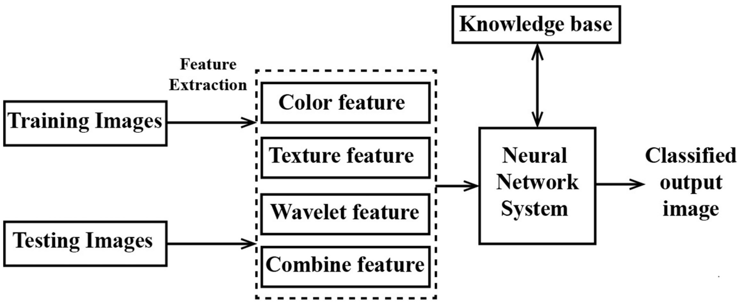
2.1 Image acquisition

Rice images of data set1 were acquired from an ordinary Nokia 6600 mobile camera with 0.3 mega pixels, VGA, 2× digital zoom, Symbian OS v7.0s and CPU running at 104 MHz. The acquired images are 640 × 460 pixels in size with 91 dpi. The images were captured with normal illumination of around 350–400 lux using T12, 40 W, 2600 lumens tube light. The rice samples of data set2 were collected from Indian Council of Agricultural Research, Imphal, India. Image acquisition was carried out under different environment. The images of data set2(a) were taken during day time under natural light using Samsung mobile camera at 0.3 mega pixels, 2× digital zoom, with image size 640 × 460 and resolution of 72 dpi, whereas the images of data set2(b) were taken using a 12 mega pixels, Nikon digital camera (Coolpix S2500) with charged coupled device (CCD) image sensor having a sensor size of 28.0735 mm^2, image size of 4000 × 3000 and resolution of 300 dpi. The images were taken under natural lighting condition during morning hour so that shadow of the camera should not appear on the image. The camera was mounted on an adjustable stand at a distance of 10 cm. The camera was set to macro mode before taking the picture, so that image can be taken from a close distance. Sample images are presented at Fig. 1.

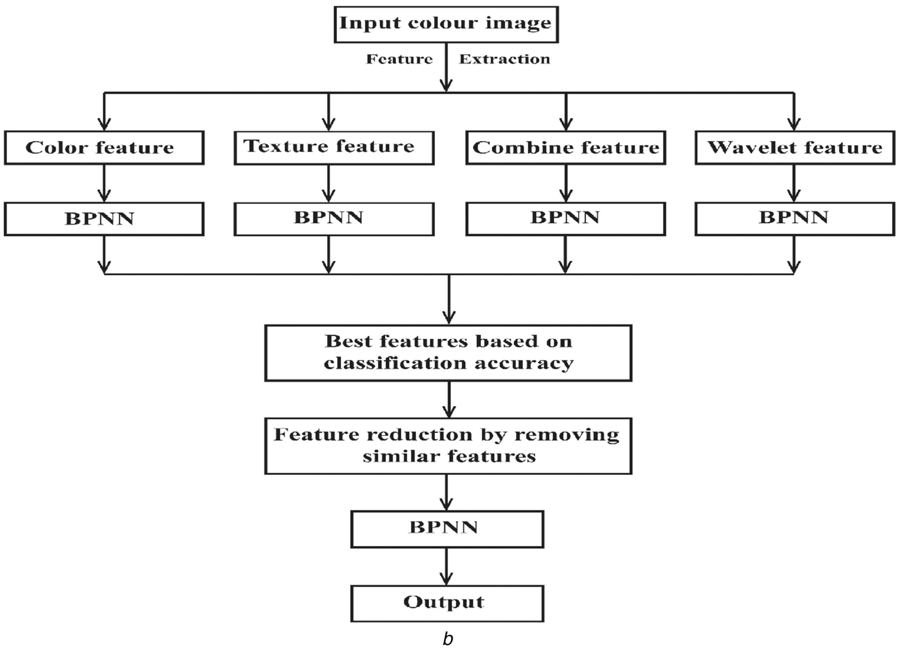
2.2 Features for classification

Three different approaches were adopted for feature extraction process. The first approach extract a total of 18 colour features from the six different colour plains (red, green, blue, hue, saturation and intensity) from the input colour image. The second approach comprises of forming grey-level co-occurrence matrix (GLCM) from each of the three image plain (R, G and B) and a total of 27 features were extracted from these three GLCM. The third approach applies wavelet decomposition on each of the three image plains (R, G and B) and a total of 24 features were extracted from the decomposed image. The above three approaches give rise to three different feature vectors of different size. Another feature vector of size 45 was formed by combining the 18 colour features and 27 texture features. Thus, we have altogether four different feature vectors or patterns for classification. A neural network model for feature extraction and classification is shown in Fig. 2*a*.

In this work, the colour images of each of the four bulk rice grain were taken and four different features, colour features, texture features, combined features and wavelet features were extracted for classification processes. The BPNN is trained separately for the above-mentioned four features and the network is tested. The classification accuracy based on all four features was



a



b

Fig. 2 *Block representation of the proposed technique*
(a) Feature extraction and classification model, ***(b)*** Feature reduction and classification process

then computed and compared base on the test result. Feature that gives the highest classification accuracy for all types of rice grain is considered for feature reduction and the other remaining three features were ignored. Feature reduction by removing similar feature elements is carried out. The BPNN performance is tested again with the reduced feature vector. Feature reduction and classification process involved in our proposed work is shown in Fig. 2*b*.

2.3 Colour feature

The use of colour in image processing is motivated by two principle factors. First, colour is a powerful descriptor that often simplifies object identification and extraction from a scene. Second, human can discern thousands of colour shades and intensities compared with about only two dozen shades of grey. Two colour models [i.e. RGB (red, green, blue) and HSI (hue, saturation, intensity)] were used for the purpose of colour feature extraction. In RGB model, each colour appears in its primary spectral components of red, green and blue. This model is based on Cartesian coordinate system. The HSI colour model decouples the intensity component from the colour carrying information (hue and saturation) in a colour image. As a result, the HSI model is an ideal tool for developing image-processing algorithms based on colour descriptions that are natural and intuitive to human [23]. Hue is the colour attribute that describe pure colour, saturation is the measure of degree to which a pure colour is diluted by white light and intensity is the degree of brightness. In order to reduce the computation time during feature extraction, the original rice images were resized to 200 × 200. The red, green and blue components were extracted from the original image. Hue, saturation and intensity were calculated from the RGB colour model [9, 20, 23]

$$H = \begin{cases} \theta, & \text{if } B \le G \\ 360 - \theta, & \text{if } B > G \end{cases} \tag{1}$$

where

$$\theta = \cos^{-1}\left\{\frac{(1/2)[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}}\right\} \tag{2}$$

$$S = 1 - \frac{3}{(R+G+B)}\{\min(R,G,B)\} \tag{3}$$

$$I = \frac{(R+G+B)}{3} \tag{4}$$

A total of 18 colour features were extracted from RGB and HSI image plains [9] which are presented in Table 1.

2.4 Texture feature

Texture is a connected set of pixels that occur repeatedly in an image. It provides the information about the variation in the intensity of a surface. To describe texture features, the most widely accepted models are those that use the co-occurrence [6, 9, 14–16]. Co-occurrence matrix method is based on the repeated occurrence of some grey-level configuration in the texture. This configuration varies slowly with distance in course texture and rapidly in fine texture. GLCM $\boldsymbol{P}_{f,d}$ (x, y), for four different values of direction 'f' (0°, 45°, 90° and 135°) and distance 'd' ($d = 1$) was calculated for each of the three image components, R, G and B

$$\boldsymbol{P}_{0,d}(x,y) = \sum_{p=1}^{n}\sum_{q=1}^{m} \begin{cases} 1, & \text{if } f(p.q) = x \text{ and if } (p, q+\Delta y) = y \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$\boldsymbol{P}_{45,d}(x,y) = \sum_{p=n}^{1}\sum_{q=1}^{m} \begin{cases} 1, & \text{if } f(p.q) = x \text{ and if } (p-\Delta x, q+\Delta y) = y \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$$\boldsymbol{P}_{90,d}(x,y) = \sum_{p=n}^{1}\sum_{q=1}^{m} \begin{cases} 1, & \text{if } f(p.q) = x \text{ and if } (p-\Delta x, q) = y \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

$$\boldsymbol{P}_{135,d}(x,y) = \sum_{p=n}^{1}\sum_{q=m}^{1} \begin{cases} 1, & \text{if } f(p.q) = x \text{ and if } (p-\Delta x, q-\Delta y) = y \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

Using these GLCM, nine texture features were extracted for each of the image plain, so a total of 27 features were extracted from R, G and B components which are presented in Table 2.

Let us now define few terms related to an image for its automated classification. Energy describes the uniformity of grey levels in the image. It is given by summation of the square elements in the GLCM, whereas the contrast feature is an indicator of the local variations. It measures the intensity contrast between a pixel and its neighbour over the whole image. Entropy on the other hand is a measure of the texture complexity. Complex textures have more entropy than simpler structure. Inverse difference moment feature indicates the amount of local uniformity in the image, whereas correlation features indicate the statistical measure of how correlated a pixel is to its neighbour over the whole image. Homogeneity provides the information of closeness of the distribution of elements in the GLCM to GLCM diagonal. Mathematically, we can express these terms as

$$\text{Mean} = \frac{\sum_{x,y} P^2(x,y)}{N^2} \tag{9}$$

$$\text{Variance} = \frac{\sum_{x,y}[P(x,y) - \text{mean}]^2}{N^2} \tag{10}$$

Table 1 List of 18 colour features

Sl. no.	Features	Sl. no.	Features
1	red mean	10	hue mean
2	red variance	11	hue variance
3	red range	12	hue range
4	green mean	13	saturation mean
5	green variance	14	saturation variance
6	green range	15	saturation range
7	blue mean	16	intensity mean
8	blue variance	17	intensity variance
9	blue range	18	intensity range

Table 2 List of 27 texture features using GLCM

Sl. no.	Features	Sl. no.	Features
1	red GLCM mean	15	green GLCM contrast
2	red GLCM variance	16	green GLCM I.D.M
3	red GLCM range	17	green GLCM correlation
4	red GLCM energy	18	green GLCM homogeneity
5	red GLCM entropy	19	blue GLCM mean
6	red GLCM contrast	20	blue GLCM variance
7	red GLCM I.D.M	21	blue GLCM range
8	red GLCM correlation	22	blue GLCM energy
9	red GLCM homogeneity	23	blue GLCM entropy
10	green GLCM mean	24	blue GLCM contrast
11	green GLCM variance	25	blue GLCM I.D.M
12	green GLCM range	26	blue GLCM correlation
13	green GLCM energy	27	blue GLCM homogeneity
14	green GLCM entropy		

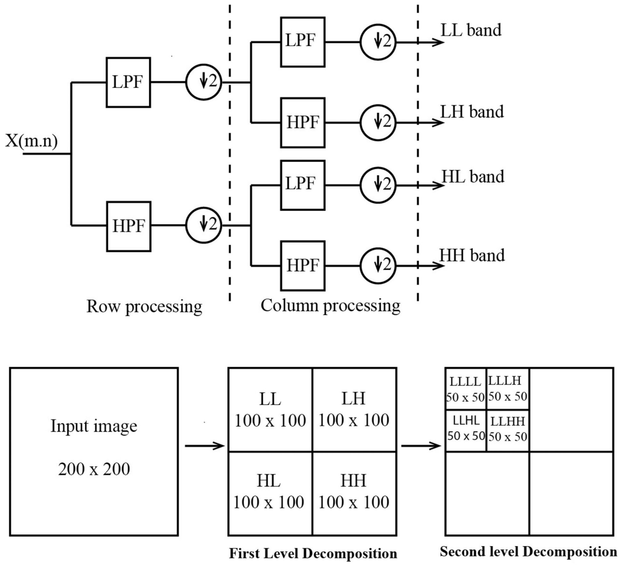


Fig. 3 *Two-level wavelet decomposition*

2.5 Wavelet feature

In discrete wavelet transform, an image signal can be analysed by passing it through an analysis filter bank followed by decimation operation. The analysis filter banks consist of a low-pass filter and high-pass filter at each decomposition stage. When the signal passes through these filters, it splits into two bands. The low-pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high-pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filter operation is then decimated by 2. First, the image is filtered along the row and then decimated by 2. It is followed by filtering the sub-image along the column and then decimated by 2. This operation splits the image into four bands, namely low low (LL), low high (LH), high low (HL) and high high (HH), respectively [1, 4, 5]. A two-level decomposition with input image size and the size of the image at different levels of decomposition were illustrated in Fig. 3. Twenty four wavelet features, eight features for each of the three colour plains are presented in Table 3.

This paper has also attempted to reduce the 24 wavelet features by discarding those features which contribute less towards classification. Fifty samples for each rice type were taken randomly and we have calculated the mean for each of the 24 features for all the four rice type (mean$[S_{m\times n}] \rightarrow [\boldsymbol{M}_{m\times 1}]$, where $[S_{m\times n}]$ is the 50 samples for one particular type of rice with $m = 24$ and $n = 50$; $[\boldsymbol{M}_{m\times 1}]$ is a column vector containing the mean of each row of S). The mean values close to each one of the rice types were determined and the corresponding features were removed from the feature vector. Thus, we were able to reduce the feature vector below 24. The most significant wavelet features and the less significant wavelet features for data set1 are presented in Table 4.

Table 3 Twenty four wavelet features

Image plain	Two-level decomposition	Image features	Image plain	Two-level decomposition	Image features	Image plain	Two-level decomposition	Image features
red plain	LLLL	1. mean	green plain	LLLL	9. mean	blue plain	LLLL	17. mean
		2. variance			10. variance			18. variance
	LLLH	3. mean		LLLH	11. mean		LLLH	19. mean
		4. variance			12. variance			20. variance
	LLHL	5. mean		LLHL	13. mean		LLHL	21. mean
		6. variance			14. variance			22. variance
	LLHH	7. mean		LLHH	15. mean		LLHH	23. mean
		8. variance			16. variance			24. variance

$$\text{Range} = \max(P) - \min(P) \tag{11}$$

$$\text{Energy} = \sum_{x,y} P^2(x,y) \tag{12}$$

$$\text{Entropy} = -\sum_{x,y} P(x,y)\log_2(P(x,y)) \tag{13}$$

$$\text{Contrast} = \sum_{x,y} |x-y|^2 P(x,y) \tag{14}$$

$$\text{Inverse difference moment} = \sum_{x,y;\, x \neq y} \frac{P(x,y)}{|x-y|^2} \tag{15}$$

$$\text{Correlation} = \frac{\sum_{x,y}[(xy)P(x,y)]) - \mu_x\mu_y}{s_x s_y} \tag{16}$$

where μ_x, μ_y are means and s_x, s_y are standard deviations defined by

$$\mu_x = \sum_x x \sum_y P(x,y)$$

$$\mu_y = \sum_y y \sum_x P(x,y)$$

$$s_x = \sum_x (x-\mu_x)^2 \sum_y P(x,y)$$

$$s_y = \sum_y (y-\mu_x)^2 \sum_x P(x,y)$$

$$\text{Homogeneity} = \sum_{x,y} \frac{P(x,y)}{1+|x-y|} \tag{17}$$

3 Classification model

Database of features were created for each data sets of rice using 400 images (100 images for each rice type). The classification was then performed for four different types of feature vectors namely, 18 colour features, 27 texture features, 45 combined features and 24 wavelet features.

3.1 Neural network classifier

Neural network architecture was designed and implemented using Matlab 2010_a software. It has been claimed in [4, 6] that BPNN is best suited for classification of agricultural products. Four layers BPNN with two hidden layers had been chosen for the classification purpose. A BPNN model with two hidden layers and four outputs is shown in Fig. 4.

The network was designed based on 45 inputs, 4 outputs with 2 hidden layers. Total numbers of hidden nodes were calculated using the equation

$$N = \frac{I-O}{2} + Y^{0.5} \tag{18}$$

Table 4 Fourteen significant features out of 24 wavelet features for data set1

Number of wavelet feature	Mean of type 1	Mean of type 2	Mean of type 3	Mean of type 4
1	**3.689112**	**3.077192**	20.88629	5.309688
2	2.446584	1.136016	9.279452	3.751727
3	4.054808	1.466272	19.45358	5.31512
4	2.646341	1.182357	7.090139	3.449722
5	4.067184	1.433544	23.40934	5.235056
6	2.67384	1.120943	9.048754	3.617179
7	4.437096	1.491088	18.77714	5.444416
8	2.962099	1.214205	6.734917	3.581011
9	72.44116	65.02899	57.22338	51.74414
10	7.532152	9.311003	11.22141	8.547856
11	35.8709	33.62156	**26.19066**	**26.63813**
12	6.039643	**5.08441**	4.156169	**5.087987**
13	40.7087	35.57015	29.13718	23.72354
14	7.14764	**5.982905**	**5.115171**	6.506531
15	34.01425	29.94662	26.98755	23.66766
16	**5.96096**	**5.419962**	4.918662	6.37911
17	101.3893	96.60008	103.7172	99.95258
18	12.06062	16.67244	15.64326	17.20721
19	40.4194	37.11315	35.62238	**37.13813**
20	**4.917064**	**4.975325**	4.62061	6.793316
21	41.60992	**36.90948**	**36.90123**	31.2559
22	**5.446084**	**6.422405**	**5.776379**	**6.720541**
23	38.03853	34.1466	32.4415	31.86289
24	**5.15018**	**5.267417**	4.999639	**5.3045**
features discarded	**1,11,12,14,16,19,20,21,22 and 24 = 10**			
features considered	**2,3,4,5,6,7,8,9,10,13,15,17,18 and 23 = 14**			

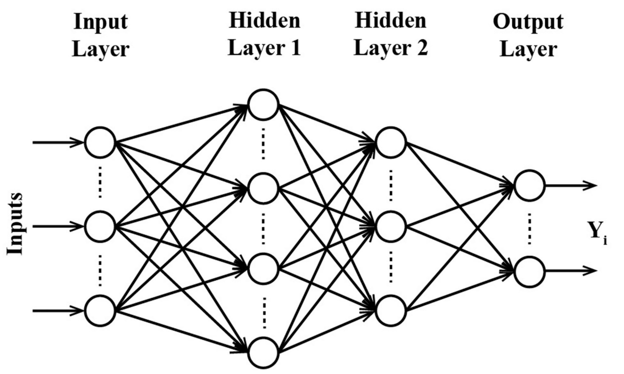


Fig. 4 *Neural network classifier model*

where N is the total numbers of hidden nodes; I is the numbers of input nodes; O is the numbers of output nodes; Y is the numbers of training patterns.

The proposed work uses the same network architecture for classification of all types of feature vectors. The BPNN was fed with 200 numbers of input patterns (50 for each rice types) where the network was designed to divide the patterns in the ratio 50:25:25 (training:testing:validation). The network automatically stops its training when any one of the following condition is satisfied:

i. When the validation is successful.
ii. When epoch reaches to 1000.
iii. When the mean square error reaches to zero.

The network is now tested using 'sim' command in Matlab neural network tool box by giving 400 test patterns (100 for each rice type).

4 Results and discussion

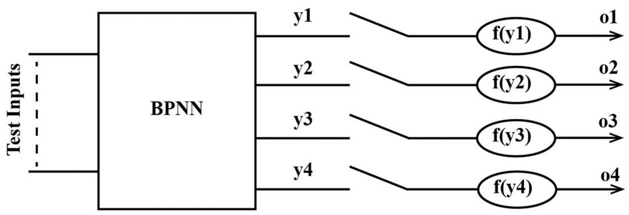


Fig. 5 *Neural network model with thresholding*

The simulation has been carried out in Matlab environment with the four different features described earlier. It is found that the BPNN was not able to converge to the given target within the specified stopping conditions. However, one can able to judge the output manually, which is again going to be a tedious work. To overcome this problem and to achieve convergence, the output of the network for a given test pattern was fed to an adaptive threshold function which is shown in Fig. 5. This thresholding arrangement produces an output which exactly matches any one of the target values that we have set during training phase (0001, 0010, 0100 and 1000)

$$O_i = \begin{cases} 1, & \text{if } y_i = y(\max) \\ 0, & \text{otherwise} \end{cases} \tag{19}$$

A performance plot for training, validation and testing of data set1 was obtained and shown in Fig. 6. Curve 3 shows the decreasing error on the training data, curve 2 shows the validation error and the training stops when validation error stops decreasing, curve 1 shows error on the test data. Results show that the GLCM method of feature extraction consumes more time compared with wavelet-based method. Time consumption (seconds) in extracting features from a single input colour image was calculated using Matlab software and is presented in Table 5 for all the three data sets. Classification accuracies for different feature vectors using different classifiers were also calculated on all the three data sets and the results are presented in Table 6. The average classification accuracy of BPNN on all four different features for data set1 was

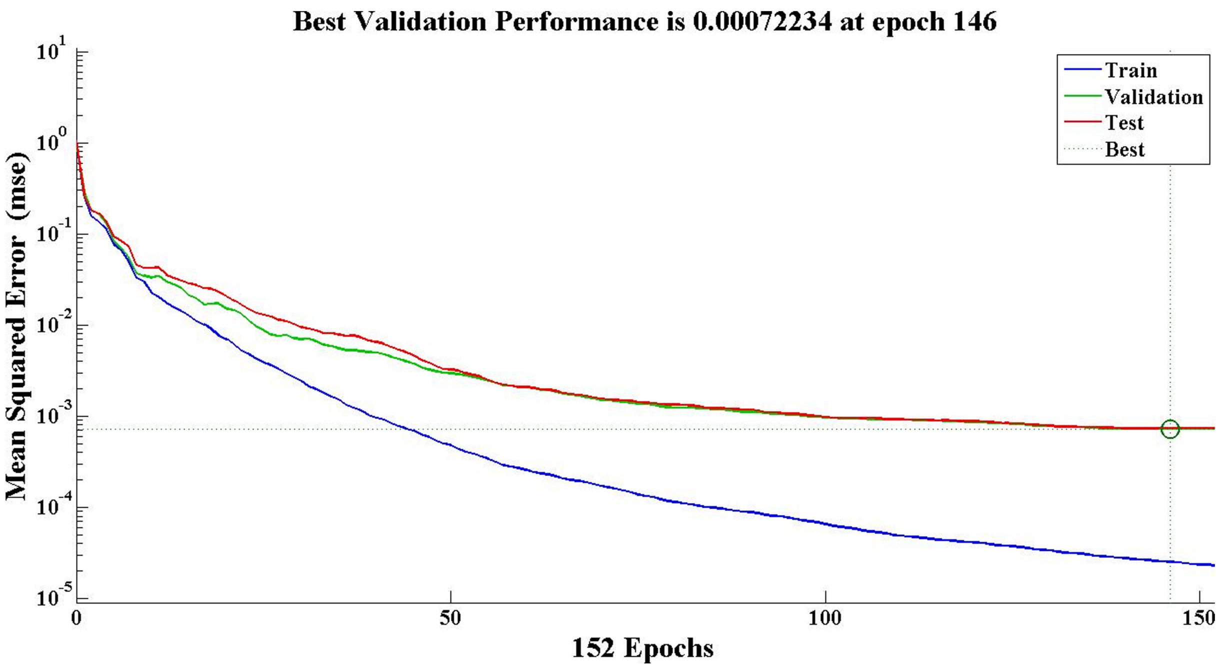


Fig. 6 *Performance plot of training, validation and testing of data set1*

Table 5 Comparison of feature extraction time in second

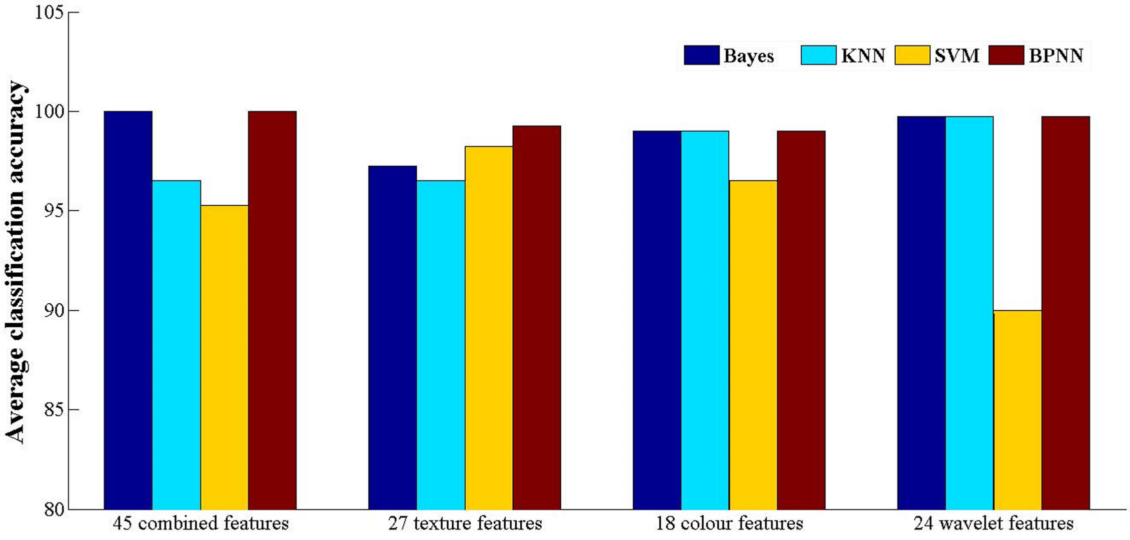
Data set	45 combined features (approximate time in seconds)	27 texture features (approximate time in seconds)	18 colour features (approximate time in seconds)	24 wavelet features (approximate time in seconds)
data set1	92.40	82.40	0.34	0.46
data set2(a)	93.93	85.76	0.34	0.49
data set2(b)	112.04	105.28	0.89	0.97

compared with other three classifiers using Matlab tools and is presented in Fig. 7*a*. Similarly for data set2(b) is presented in Fig. 7*b*. Classification based on selected features was also calculated and is presented in Table 7. The average classification accuracy of BPNN based on reduced features on all data sets were compared with other classifiers and the same is presented in Fig. 8*a*. In most of the cases, as we increase the number of features the system will be able to classify more accurately. However, the main objective of the work is to reduce the number of features without compromising the classification accuracy. The same can be seen from Tables 6 and 7, where the classification based on reduced features also shows equal level of accuracies. Thus, it can be concluded that reducing the feature size does not degrade the classification accuracy in this proposed work. Results also show that the proposed BPNN with adaptive thresholding produces consistently better result as compared with other classifiers and the same is presented in Fig. 8*b*. It is worth mentioning that classification accuracy with 18 colour features should be selected for feature reduction in case of data set2(b) which is clear from Table 6. It is also seen from the results of data set1 and data set2(a) that wavelet-based feature reduction and classification gives the better results as compared with other features. This is because the images of the above-mentioned data sets contain multiple frequency components as compared with image of data set2(b), which is a sharp image wherein low-frequency components are less.

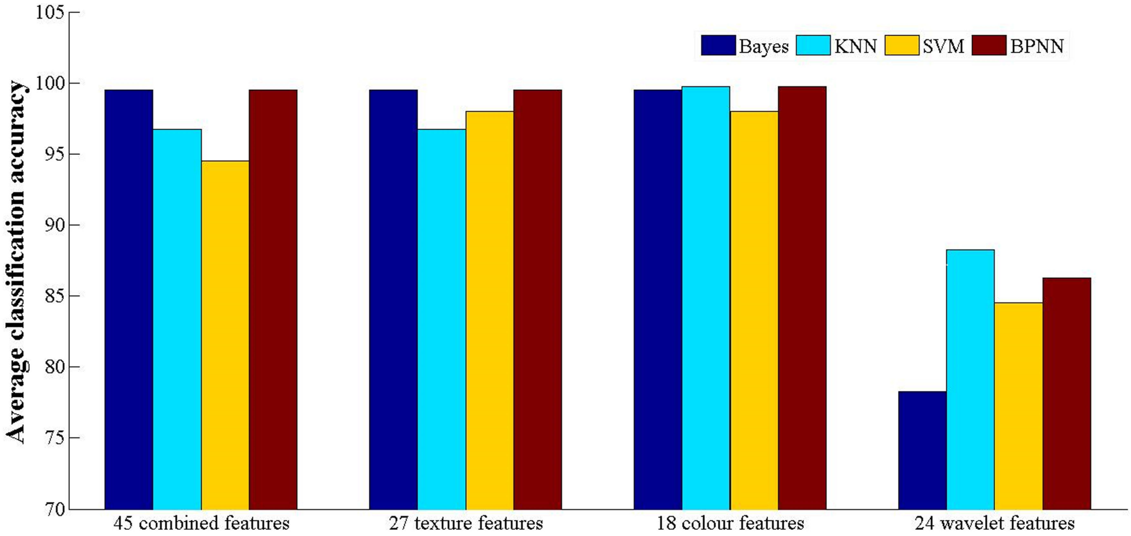
Table 6 Classification accuracies of all four different features on three different data sets

	Classification accuracy															
	45 features				27 features				18 features				24 features			
	Bayes	KNN	SVM	BPNN	Bayes	KNN	SVM	BPNN	Bayes	KNN	SVM	BPNN	Bayes	KNN	SVM	BPNN
Data set1																
TYPE1	100	100	97	100	100	100	100	100	100	100	100	100	100	100	87	100
TYPE2	100	92	84	100	89	93	93	97	98	98	88	98	100	100	81	100
TYPE3	100	99	100	100	100	98	100	100	98	98	98	98	99	99	100	99
TYPE4	100	95	100	100	100	95	100	100	100	100	100	100	100	100	92	100
Data set2(a)																
TYPE1	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
TYPE2	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
TYPE3	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
TYPE4	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Data set2(b)																
TYPE1	99	97	89	100	99	97	94	100	99	100	98	100	82	94	70	95
TYPE2	100	98	98	99	100	98	98	99	100	100	98	100	70	90	86	86
TYPE3	100	99	91	100	100	99	100	100	100	100	96	100	90	88	82	86
TYPE4	99	93	100	99	99	93	100	99	99	99	100	99	71	81	100	78

KNN, *k*-nearest neighbour.



a



b

Fig. 7 *Comparison of average classification accuracies of all four classifiers based on different features*
(a) Comparison of average classification accuracies of all classifiers on four different features of data set1, ***(b)*** Comparison of average classification accuracies of all classifiers on four different features of data set2 (b)

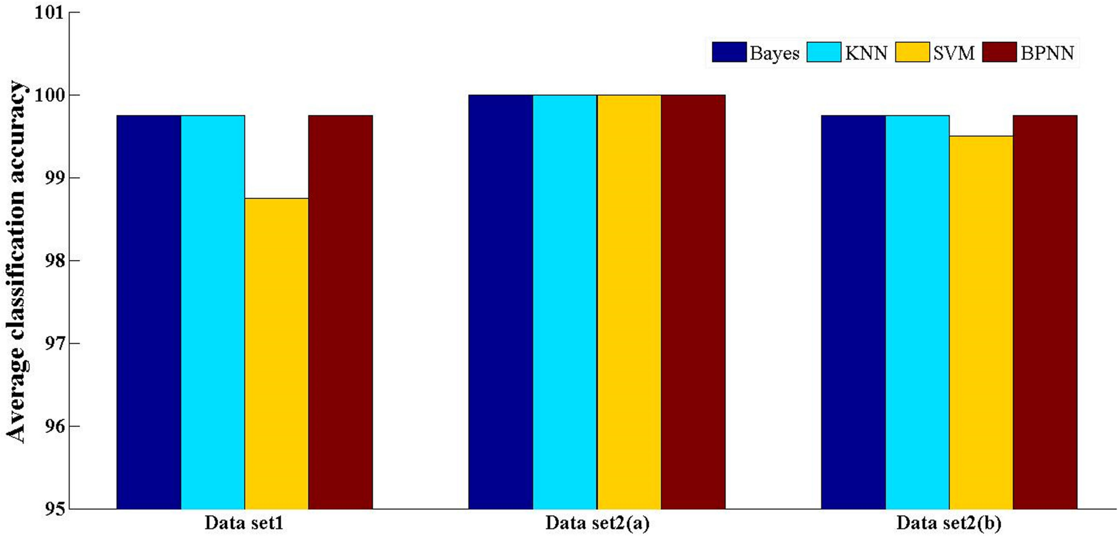
5 Conclusion

The classification of different types of rice grains using BPNN was successfully achieved using different feature vectors. Results show that classification using reduced wavelet features was able to achieve an accuracy level very close to that of unreduced features in case of data set1 and 2(a). It is found that BPNN with adaptive thresholding gives consistently better results for all three data sets as compared with other three classifiers. The proposed feature reduction technique can also classify rice grains without degrading the classification accuracy even with a lesser number of features. Results show that classification based on wavelet features gives better results for unsharp image data, whereas colour features found to be more suitable for sharp image data. It can also be inferred from the result that BPNN is the appropriate choice in our proposed work which gives an average classification accuracy of 99.5% (for data set1), 100% [for data set2(a)] and 96.25% [for data set2(b)] while considering all four different features.

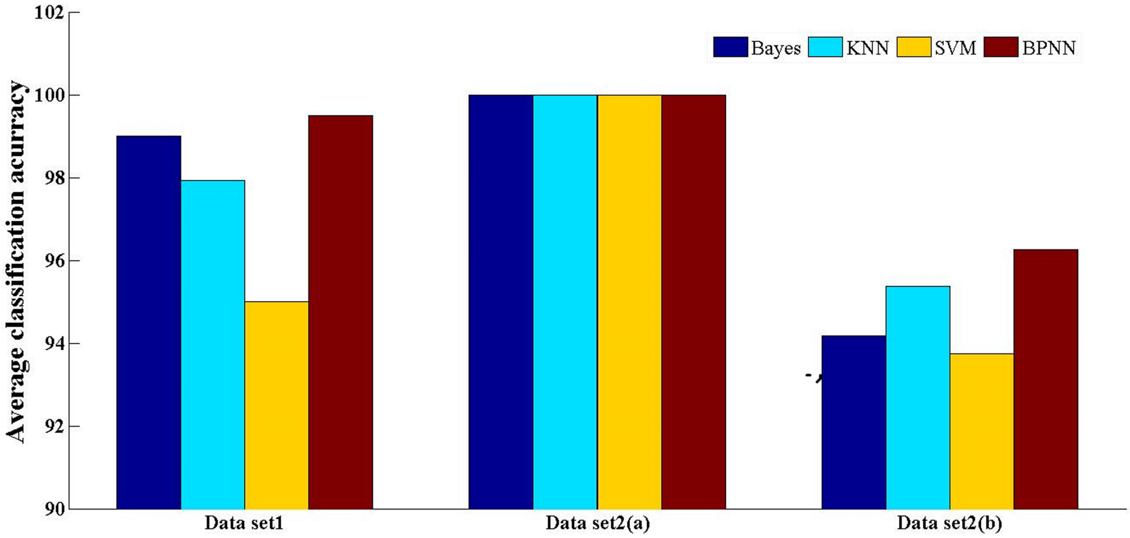
Table 7 Classification accuracies for all data sets using selected features

Grain types	Classification accuracy on selected features											
	Data set1: 14 wavelet features				Data set2(a): 9 wavelet features				Data set2(b): 11 colour features			
	Bayes	KNN	SVM	BPNN	Bayes	KNN	SVM	BPNN	Bayes	KNN	SVM	BPNN
TYPE1	100	100	100	100	100	100	100	100	100	100	98	100
TYPE2	100	100	96	100	100	100	100	100	100	100	100	100
TYPE3	99	99	99	99	100	100	100	100	100	100	100	100
TYPE4	100	100	100	100	100	100	100	100	99	99	100	99

KNN, *k*-nearest neighbour.



a



b

Fig. 8 *Comparison of average classification accuracies of all four classifiers on all data sets*
(a) Comparison of average classification accuracies of all classifiers on reduced features, ***(b)*** Comparison of overall average classification accuracies of all classifiers on all data sets considering all four features

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