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A COMPARISON OF GRAY-LEVEL RUN LENGTH MATRIX AND GRAY-LEVEL CO-OCCURRENCE MATRIX TOWARDS CEREAL GRAIN CLASSIFICATION

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ABSTRACT

This study describes a comparison of texture features based on Gray Level Co-Occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) towards bulk grain classification. In order to have a fair comparison, four features were extracted each from GLCM and GLRLM. A total of 400 bulk grain colour image were taken for 4 different verities of rice (100 for each rice type). A Back-Propagation Neural Network (BPNN) with adaptive thresholded output is used for classification. The network was trained with 200 image samples (50 for each rice type) and the same is tested with all the 400 images. It is found that the average classification accuracy base on GLRLM texture features using BPNN is 99.5%, which is better as compare to that of GLCM texture features having a average classification accuracy of 97.75%. The classification accuracy using BPNN was also compared with other classifiers like K-NN and SVM. Results shows that BPNN provides better consistency in classifying rice grain as compare to K-NN and SVM.

Key words: Co-Occurrence Matrix, Run length Matrix, Texture Features, Back Propagation Neural Network.

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1. INTRODUCTION

Machine vision becomes one of the related fields of image processing and image understanding. It encompasses image acquisition, image interpretation, image analysis, features extraction etc. machine vision are also used mostly for inspection of large numbers of agricultural and industrial products in order to achieve desire quality controls. Machine vision has also become an alternative to inspection and grading of agricultural products, which is really a tiresome task for human. It is also studied that classification and grading of agricultural products are not that simple as unlike other industrial products because of the fact that the colour, texture and morphology of agricultural products are not governed by a unique mathematical function [4,10, 13]. Thus it becomes a challenge to classify naturally varying appearance of biological entities [4,10]. A human based grain handling process involves a very time consuming and tiresome task, also the inspectio n processes may vary from one person to another. The grain inspector indeed should have a very good eye sight. The quality of grain handling may also decline slightly from time to time base on the mood and fatigueness of the grain inspector. In this context a machine vision system can mimic the whole process in an efficient manner without compromising the accuracy. Also a machine vision system can provides consistency in the processes of grain handling unlike human. In most research classification of cereal grain were carried out based on single grain kernel, which requires arrangement of grain kernel in a non touching fashion and also requires excellent image acquision setup [4,5,7,10,11,13]. Classification of cereal grain based on single kernel is quite possible in laboratory but not an easy option to be implemented on site [6,13]. The above mentioned problems can be solved if classification is carried out on bulk grain samples [3,6]. Features extraction for image classification in most of the published works was based on the combined properties of both GLCM and GLRLM [3,5,6,7]. Studies were also carried out for classification of cereal grain using GLCM properties alone as texture descriptor [8,9,12,13]. Studies has not been made or attempted to compare the strength of CLCM properties and GLRLM properties towards cereal grain classification. This study describes a comparison of GLCM and GLRLM properties as texture descriptors for rice grain classification using artificial neural network. The classification involves (1) Image acquisition using digital camera (2) Features extraction using GLCM and GLRLM (3) classification based on GLCM and GLRLM separately and (4) comparing the classification accuracy

2. MATERIALS AND METHODS

2.1. Image acquisition

Image were acquired using Nikon digital camera (Coolpix S2500) with charged coupled device (CCD) image sensor having a sensor size of 28.0735 mm2, image size of 4000x3000 and resolution of 300 dpi. The images were captured with natural lighting condition during morning hour so that shadow of the camera should not appear on the input 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 closer distance. Sample of bulk rice images are presented at Fig.1

Figure 1 Samples of rice colour image

2.2. Texture features for classification

This paper deals with the extraction of the texture features based on Gray Level Co-occurrence Matrix and Gray Level Run Length matrix. A Gray Level Co-occurrence Matrix provides the information about how frequently a pair of pixels occurs in an image towards a particular direction. If the input image is of size PxQ and has a maximum gray level say 'L', then the size of the GLCM will be LxL. Thus care must be taken regarding the pixel intensity, as the pixel intensity is large the resulting GLCM will also be large and takes more time to execute. On the other hand a Gray Level Run Length Matrix provides information about the connected length of a particular pixel in a definite direction. If PxQ be the size of the input gray scale image having a maximum gray level say 'L', then the resulting Gray Level Run Length Matrix for this input image is LxQ. An example of GLCM and GLRM is shown in Fig.2. An overall classification process along with texture feature extraction using GLCM and GLRLM is placed at Fig.3.

1	2	2	4
1	1	3	4
2	3	1	4
4	1	3	1
2	3	1	1

Input of size 5x4

	1	**2**	**3**	**4**
1	2	1	2	1
2	0	1	2	1
3	3	0	0	1
4	1	0	0	0

GLCM of size 4x4

1	2	2	4
1	1	3	4
2	3	1	4
4	1	3	1
2	3	1	1

Input of size 5x4

	1	**2**	**3**	**4**
1	4	2	0	0
2	2	1	0	0
3	4	0	0	0
4	4	0	0	0

GLRLM of size 4x4

Figure 2 Example of GLCM and GLRLM

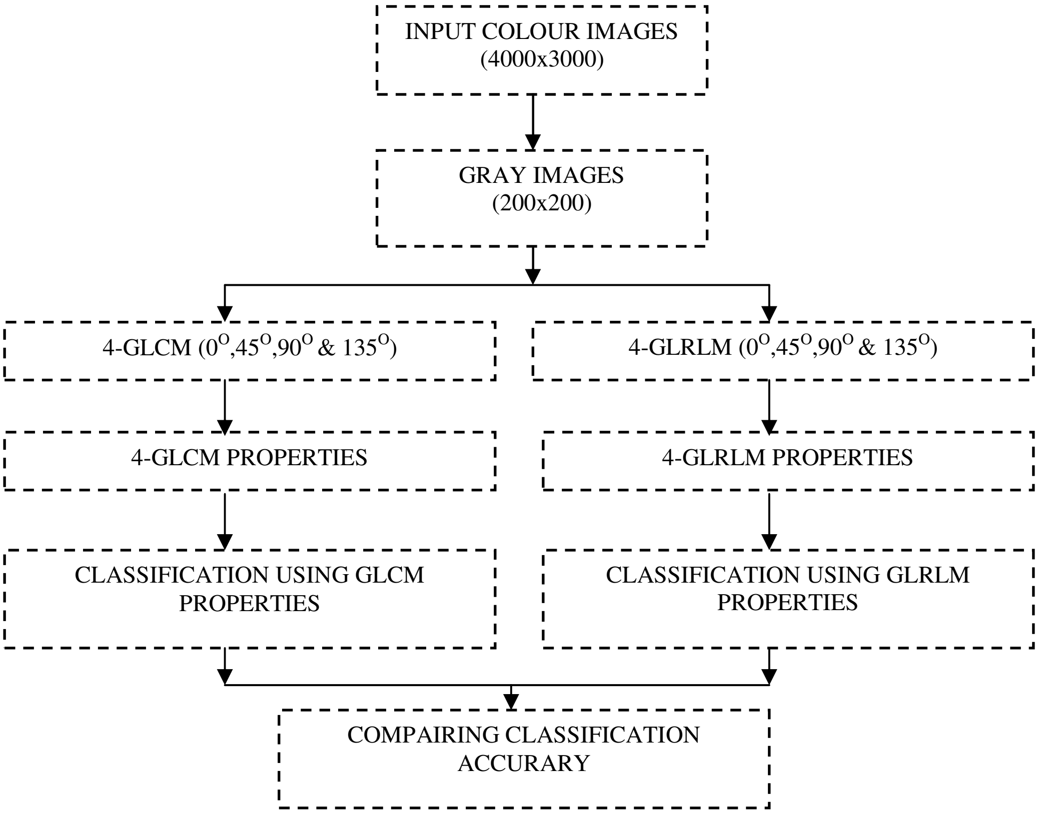


Figure 3 Block diagram of the proposed feature extraction and comparison.

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 matrix and run length matrix [3,5,6,7]. Co-occurrence matrix method is based on the repeated occurrence of some gray level configuration in the texture. This configuration varies slowly with distance in course texture and rapidly in fine texture. Gray level co-occurrence matrix (GLCM) $P_{f,d}(x, y)$,for four different direction 'f' (0^o, 45^o,90^o and 135^o) and distance 'd' (d=1) were calculated from the gray scale image[13]. The gray level for the input gray scale image was set to 64. We have 4 GLCM matrixes for 4 different directions. The average of all these matrixes was derived by adding all the pixels of the 4 GLCM and finally divided by 4, so we have a single averaged GLCM matrix. The following four properties were extracted from the above mentioned matrix, P(x,y) [13].

$$\text{Energy} = \sum_{x,y} P^2(x,y) \tag{1}$$

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

$$\text{Correlation} = \frac{\sum_{x,y} [(xy)P(x,y)]) - \mu_x \mu_y}{s_x s_y} \tag{3}$$

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

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

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

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

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

$$\text{Homogeneity} = \sum_{x,y} \frac{P(x,y)}{1+|x-y|} \tag{4}$$

For a given image, a run length matrix *P(i,j)* is define as the number of runs with pixels of gray level *i* and run length *j* [1,2]. Four texture features namely, Short run low gray-level emphasis, Short run high gray-level emphasis, Long run low gray-level emphasis, and Long run high gray-level emphasis were extracted from the gray scale image of bulk grain [1,2]. Here also the gray level for the input gray scale image was set to 64. We have 4 GLRLM matrixes for 4 different directions. The average of all these matrixes was derived by adding all the pixels of the 4 GLRLM and finally divided by 4, so we have a single averaged GLRLM matrix. The following four properties were extracted from the above mentioned matrix, *P(i,j)*.

$$\text{SRLGE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{i^2 . j^2} \tag{5}$$

SRHGE= $\frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j).i^2}{j^2}$ (6)

LRLGE= $\frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j).j^2}{i^2}$ (7)

LRHGE= $\frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}p(i,j).i^2.j^2$ (8)

Where P(i,j) is the run length matrix and n_r is the total number of runs.

3. CLASSIFICATION MODEL

Data base of texture features base on GLCM and GLRLM were created for each category of rice using 400 images (100 images for each rice type). The classification of the four verities of rice was then performed based on four GLGM texture features and the same was performed on four GLRLM texture features. The classification accuracy of these four verities of rice grain based on GLCM features and GLRL features were compared using different classification models.

3.1. Neural network classifier

Neural network architecture was designed and implemented using Matlab 2010_a software. It has been claimed in [6] that Back propagation neural network (BPNN) is best suited for classification of agricultural products. Four layers BPNN with 2 hidden layers had been chosen for the classification purpose. A Back Propagation Neural Network Model with two hidden layers and four outputs is shown in Fig.4.

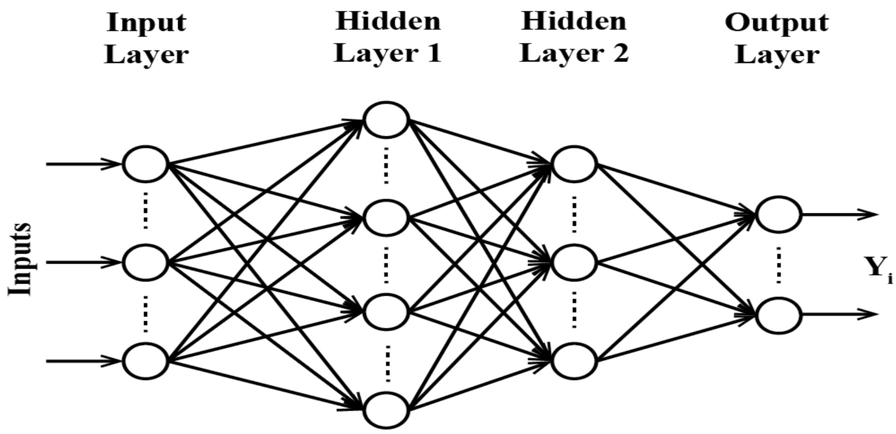


Figure 4 Neural network classifier model

The network was designed based on 4 inputs, 4 outputs with two hidden layers. Total numbers of hidden nodes were calculated using the equation [5,6,13].

$$N = \frac{I - O}{2} + Y^{0.5} \quad (9)$$

Where, N – Total numbers of hidden nodes, I – Numbers of input nodes,
O – Numbers of output nodes, Y – Numbers of training patterns

The same network architecture was used for classification purpose in the proposed work. The BPNN was fed with 200 numbers of input patterns, where the network was designed to divide the patterns in the ratio 70:15:15 (training: testing: validation). 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

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 again. 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 produce an output which exactly matches the corresponding target values that we have set during training phase.

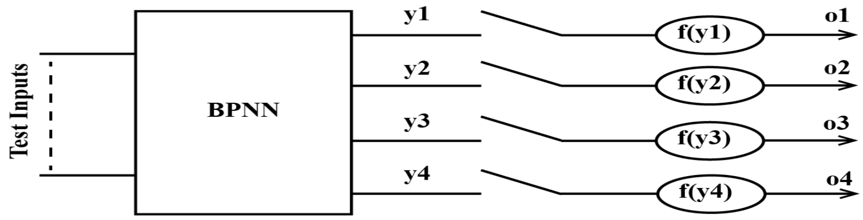


Figure 5 Neural network model with thresholding

$$O_i = \begin{cases} 1 & \text{if} \quad y_i = y(\max) \\ 0 & \textit{otherwise} \end{cases} \tag{10}$$

Table 1 Comparison of Classification accuracies

GRAIN TYPES	K-NN		SVM		BPNN	
	4 GLCM features	**4 GLRLM features**	**4 GLCM features**	**4 GLRLM features**	**4 GLCM features**	**4 GLRLM features**
TYPE1	87	99	94	99	96	99
TYPE2	96	100	100	100	100	100
TYPE3	92	100	96	99	96	99
TYPE4	81	100	99	100	99	100

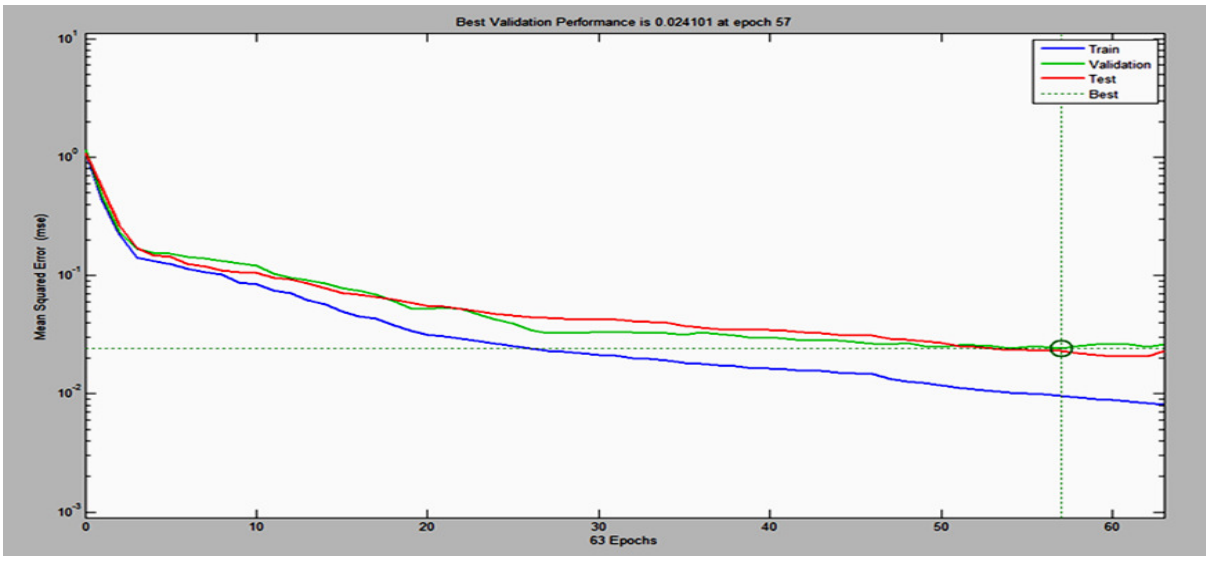
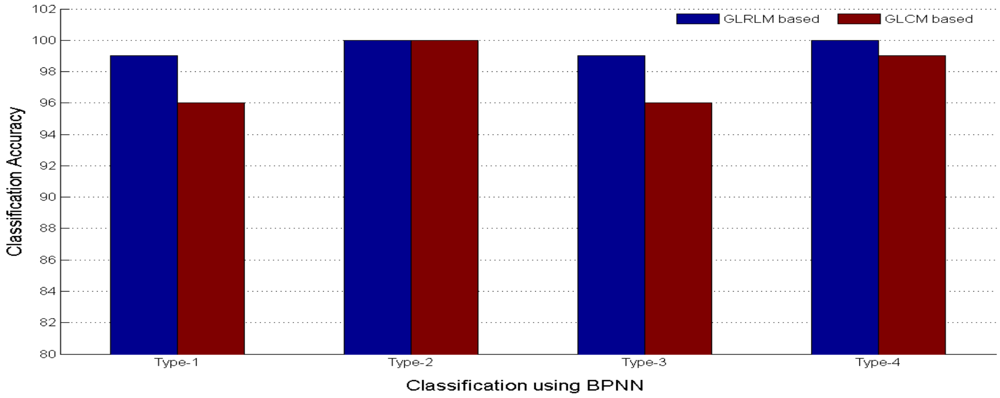
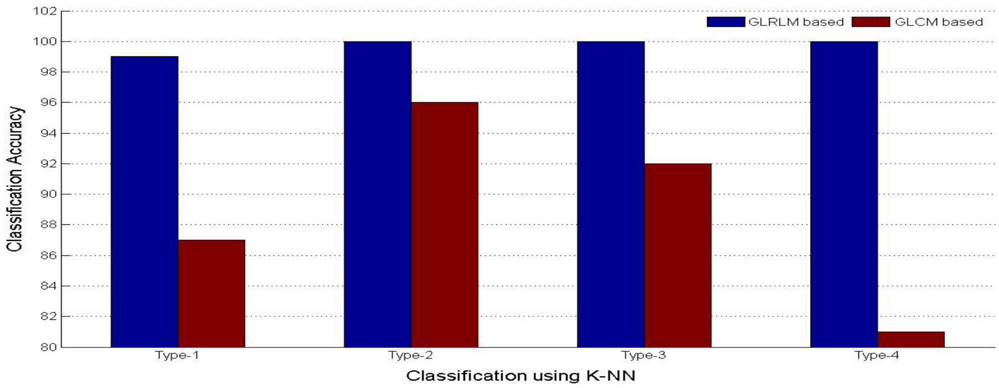


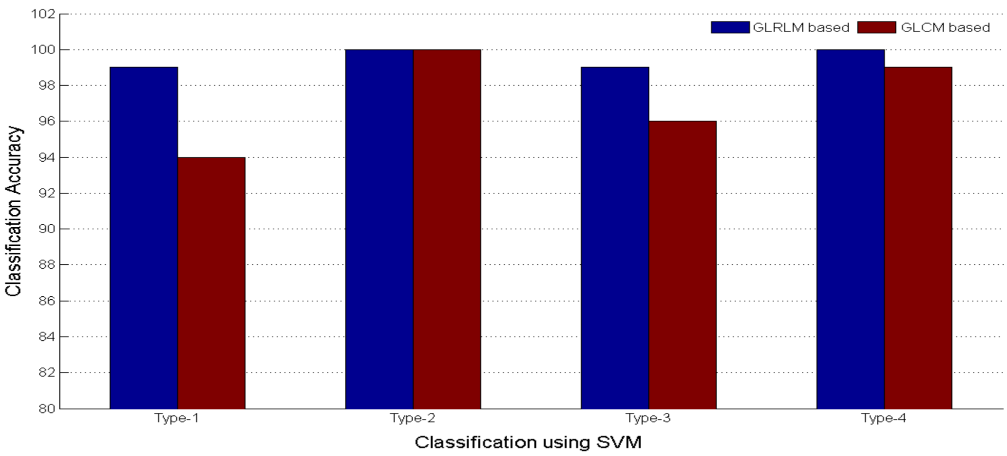
Figure 6 Performance plot of training, validation and testing



(a)



(b)



(c)

Figure 7 Comparison of classification accuracy

A Performance plots for training, validation and testing were obtain using MATLAB software and the same is shown in fig.6. Blue line shows the decreasing error on the training data, green line shows the validation error and training stops when validation error stops decreasing, red line shows error on the test data. Result of this study is presented in table 1. Result shows that classification of bulk rice grain using GLRLM features is better as compare to GLCM features. Classification accuracies base on GLRLM features and GLCM features using different classifiers were also presented in figure 7. It can be inferred from figure 7 (a,b,c) that, the GLRLM features gives better classification accuracy as compare to GLCM features on all three classifiers (BPNN,K-NN,SVM). The overall classification accuracy using BPNN on GLRLM features is found to be 99.5% and that of GLCM features is 97.75% which is consistent as compare to other Classifiers.

5. CONCLUSION

The classification of different rice grain types using GLRLM features and GLCM features was successfully carried out and the results were compared. Results shows that GLRLM features outperforms GLCM features in our area of bulk rice grain classification and the same holds good for all three types of classifiers. It's also found that K-NN classifier provides better classification accuracy in case of GLRLM features, giving an average classification accuracy of about 99.75 which is the highest as compare to SVM and BPNN. But at the same time its classification accuracy based on GLCM features is quite poor, having an average classification accuracy of 86.5% which is lowest as compare to the other two classifiers. Results show that classification using BPNN is consistent for both GLRLM features and GLCM features. This study found GLRLM features quite appropriate as compare to GLCM features in our area of rice grain classification.

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