Adaptive threshold back propagation neural network for rice grain classification using variance and co-variance colour features

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Abstract

This paper presents a simple and fast feature extraction technique for classification of four varieties of rice grain. Three colour models (RGB, HSV and HSI) are obtained from the input colour images. Variance and Covariance features are then extracted from each of the three colour models. The classification of rice grains are then carried out using a Back Propagation Neural Network with adaptive thresholding. The computational time for feature extraction and their classification accuracies are also compared with other feature extraction techniques. It is found that the time taken using variance and covariance features extraction technique is relatively less compared to other feature extraction techniques. It is also seen that the proposed feature extraction technique is able to achieve better classification accuracy as compared to other feature extraction techniques discussed in this paper. Results suggest that the proposed technique is able to yield higher classification accuracy than that of other statistical classifiers like K-Nearest Neighbour (K-NN), Naïve Bayes and Support Vector Machine (SVM). The performances of all four classifiers were also tested against standard data sets.

Keywords: Image, Colour, Features, Variance, Co-variance, Neural Network

I. Introduction

Digital image processing encompasses processing of pictorial information for human interpretation, storage and transmission. An image is nothing but a 2-D function, I(p,q) where p and q are spatial coordinates and ‘I’ the intensity of the image at that point. For a digital image the intensity value and the coordinates are all finite discrete quantities [XXXII], [XXXVIII]. In digital image input is an image and output may be image or some attributes of image. Now-a-days digital image processing has impacted in almost all fields of Engineering. Image analysis or understanding becomes an important steps and lies between image processing and computer vision. The ultimate goal of computer vision in cereal grain classification is to mimic human visual response, able to learn and make decision based on perceived
visual information. Computer vision thus can be used to monitor and inspect industrial products in order to achieve desire quality controls. Now a-days application of computer vision in agriculture sector has become an important research area for inspection and quality control of agricultural products. It is studied that the visual appearance of agricultural products are difficult to represent by a specific mathematical function [XIII],[XIX] and thus it is not an easy task for the computers to identify this naturally varying agricultural products. Inspection of grain samples for classification and grading become quite tedious and time consuming when performed manually, moreover there is also chance of having human error due to fatigue, eyesight and continuous hour of working. Works related to classification based on Single grain kernel are presented in [I],[III],[VI],[XI],[XIII],[XIX],[XX],[XXII],[XXVI],[XXXIII],[XL-XLIII]. Such classifications mostly use morphological features which involves arranging the kernel in a non-touching manner. This also involves image pre-processing steps like image segmentation, removing of unwanted objects like back-ground, followed by extraction of object of interest from the input image. Classification based on single grain kernel is quite suitable in laboratories with proper image acquisition setups, but may not be an easy option to implement on site [VIII],[XXX]. In case of bulk grain classification, some of the pre-processing steps of digital image processing will not be required. Moreover the system will not require any extra provision to arrange the grain kernel in a non-touching fashion [IV],[XXIII], [XXXIX]. Different characterization models based on colour and texture are also presented in [VIII], [IX], [XX], [XXIII], [XXX], [XXXIII], [XXXIX], [XLIII]. Cereal grain classification based on bulk grain using features derived from colour and textures are carried out in [VIII], [XV], [XXIII], [XXX], [XXXI], [XXXIX]. Cereal grain classification using support vector machine and other statistical classifiers are also discussed in [VII], [IX], [X], [XI], [XXXV]. Various classification tasks based on texture features are also presented in [XVII], [XXIV], [XVIII], [XXIX], [XXXIV], [XLIV], [XLV]. Applications of image processing and computer vision in identification and classification of various food products are also presented in [II], [V], [XI], [XXI], [XXV], [XXVII], [XXVIII], [XXXVI], [XXXVII]. It is seen that the size of the feature vector also decides the classification accuracy, as too many redundant features occupy more memory and takes longer time to extract features. Moreover it does not guarantee higher classification accuracy [XXVI], [XLVI]. It is rather simple to design a classifier with less number of inputs as compare to those with more number of inputs. This paper presents classification of four types of rice with limited features using variance-covariance matrix. A multilayer Back Propagation Neural Network with adaptive thresholding is used for this work. The proposed model involves four steps, first step discussed about image acquisition, second step talks about feature extraction, third steps regarding classification and finally comparison of the classification accuracies with other feature extraction techniques and also with other standard classifiers. This paper is organized as follows: Section II describes materials and methods used for classification purpose. Section III discuss about the proposed technique. Section IV presents a neural network classification model. Section V discussion on the results obtained and Section VI concludes the work.
II. Materials and methods

This section discussed about the process of acquiring rice colour images and extracting different features from the acquired image.

Image acquisition

Three different data sets of bulk rice grain samples are considered in this work for classification purpose. The images are taken under different environmental conditions. The images of data set1 were acquired using an ordinary Nokia 6600 mobile camera with 0.3 mega pixels.

The images were captured under normal lighting condition using T12, 40W, 2600 lumens tube light. The images of data set 2(a) and 2(b) were taken using two different cameras under natural light during day time. Images of data set2(a) were captured using a Samsung mobile camera at 0.3 mega pixels whereas images of data set2(b) were captured using a 12 mega pixels, Coolpix S2500, Nikon digital camera. A simple image acquisition setup with vertically adjustable camera stand having a fixed platform is used for mounting the camera. The distance between the camera and target were maintained at 10 cm. The images were taken in macro mode. Sample images are shown in Fig.1.

Features for classification

Once the images are acquired, the next step is to extract the attributes of the image, which can best distinguish one image from the other. Here we have extracted three different features namely, colour, texture and variance-covariance features. Eighteen colour features were extracted using RGB and HSI colour models. Twenty seven texture features were extracted using Gray Level Co-occurrence Matrix at 0°, 45°, 90° and 135°. Forty five combined features of colour and texture are also obtained. The above mentioned feature extractions are presented in [VIII]. The present method of feature extraction in this work involves simple steps of obtaining three numbers of [3x3] variance-covariance matrices each from the three colour model namely, RGB, HSV and HSI respectively.

Fig 1. Sample images
III. Proposed technique

The proposed technique of feature extraction involves acquiring a colour image of bulk rice grain. The input colour images are then resized to [200x200] so as to reduce the computational time for extraction. From the resized image, RGB, HSI and HSV colour components are extracted. A variance –covariance matrix, for each of these three colour models are then extracted. The computational time to extract the features is also computed and compared with other feature extraction techniques namely, colour and texture. The above features are then used for the classification purpose, which involves four different classifiers and the same is presented in Fig. 2. Based on the classification accuracy achieved using BPNN classifier, best feature extraction technique is selected. Features with less number of feature vectors and having higher classification accuracies are considered for further classification purpose.

Fig 2. Block representation of the proposed technique

Variance and co-variance features

A variance-covariance matrix based feature extraction approaches are incorporated in this work to extract the three variance features and three co-variance features from the input colour images of the bulk rice grains.

**RGB to HSV conversion:**

\[
\begin{align*}
\text{Max} &= \text{Max}(R, G, B) \\
\text{Min} &= \text{Min}(R, G, B) \\
V &= \text{Max} \\
S &= \frac{\text{Max} - \text{Min}}{\text{Max}}
\end{align*}
\]
If $H < 0$, then $H = H + 1$

A $[3x3]$ variance-covariance matrix is then generated for each of the three colour models (RGB, HSV and HSI). Thus, altogether we have three variance–covariance matrices for all three colour models. The HSV and HSI colour planes are obtained from the RGB planes using the following relationships [VI],[VIII],[XV].

**RGB to HSI conversion:**

$$H = \begin{cases} 
\theta & \text{if } B \leq G \\
360 - \theta & \text{if } B > G 
\end{cases} \quad (6)$$

where,

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

$$S = 1 - \frac{3}{(R+G+B)} \{ \min(R,G,B) \} \quad (7)$$

$$I = \frac{(R+G+B)}{3} \quad (8)$$

$$\sum = \frac{1}{N} \sum_{i=1}^{N} (X_i - \bar{X})(Y_i - \bar{Y}) \quad (9)$$

Where, $\sum$ represents variance co-variance matrix, N is the number of pixels in each of the colour planes for a particular colour model, X and Y indicate any of the two colour planes for a particular colour model. $\bar{X}$ and $\bar{Y}$ are the means of each of the two colour planes, X and Y. From the colour image of bulk rice, RGB, HSV and HSI colour planes are extracted. A $[40000x3]$ matrix is generated from the RGB colour space, such that each of the three columns represents R, G and B planes respectively. A variance-covariance matrix of size $[3x3]$ is then generated from the $[40000x3]$
matrix using equation (9). Three variance features and three covariance features are extracted from each of the matrix.

![Diagram](image)

**Fig 3.** Generating Variance-covariance matrix from RGB colour plains

The variance features are the three diagonal elements of the variance-covariance matrix and any of the three off-diagonal elements that lies below or above the diagonal are the co-variance features. The process involved in extracting variance-covariance features for RGB colour model is presented in Fig.3.

### IV. Neural network classifier

A BPNN is used for the classification of four varieties of bulk rice using the features discussed in sections 2 and 3. The classification is performed using 400 images (100 for each variety). The Back Propagation Neural Network is designed with 2 hidden layers using MatLab R2013a. The numbers of hidden nodes for the classifier are calculated using equation (10).

\[
N = \frac{I - O}{2} + Y^{0.5}
\]

(10)

Where, N represents nodes in the hidden layers; I represents number of inputs; O represents the number of output and Y is the number of training patterns [VIII],[XXX]. A model of the BPNN is shown in Fig. 4. The network is trained with 200 patterns (50 for each rice variety).
The output of the network is then adaptively thresholded using equation (11), so that the output may converge to any of the target which was set during training (i.e. 0001 for rice variety 1; 0010 for rice variety 2; 0100 for rice variety 3; 1000 for rice variety 4). The network is tested with 400 images taking 100 images for each rice variety.

V. Results and discussion

Classification of four varieties of bulk rice grains based on three different data set are carried out using four different classifiers in Matlab R2013a. An adaptive thresholding function is introduced at the output of the BPNN so that the network can produce outputs of the form which we have used during training; otherwise the outputs may be any numbers between -1 to 1 and thus the result may be misleading. The performance plot and training state of the BPNN based on three variance (RGB) features is presented in fig.6 (a-b), figures shows that the training stops at 97 epoch as the validation check has failed consecutively for six times. The time required for features extraction proposed in this work is also computed and compared. It is found that the feature extraction time using variance and co-variance feature is less compared to all other techniques using 18 colour features and 27 texture features. The feature extraction time based on 64 bit Intel (R) core (TM), i7-4770 CPU, 3.40 GHz with 4GB RAM, for different feature extraction techniques are also presented in table 1. The classification accuracy for all different features on data set1 using BPNN is given in table 2. Similarly, the classification accuracy for the data set 2(a) and data set 2(b) are also presented in table 3 and 4. From table 2, 3 and 4, best features are selected based on the size of the features and classification accuracy. It is found that the variance features using HSV and HSI are able to give 100% classification accuracy with a minimum of three features. Similarly, the HSI covariance features are also able to classify with 100% accuracy with just 3 features and therefore these features are being selected for classification purpose. The selected features for data set 1 are presented in table 5 and that for data set 2(a) and 2(b) are presented in table 6 and 7 respectively. From the selected features of each data set, we have taken only those features that are common to all the three data sets. The common features with
their average classification accuracy based on four different classifier using variance and co-variance features are also presented in table 8 and it is found that BPNN is able to classify all four variety of rice with 100% accuracy unlike that of other features presented in table-9. The average classification accuracy of all three data sets using variance and co-variance features are also presented in fig. 5 and that using other features is presented in fig. 6. From these two figures, it is found that variance and co-variance features can provide 100% classification accuracy on the three data sets using BPNN. For better generalization, the performances of all the four different classifiers discussed in this paper were also tested against three standard datasets from the University of California, Irvine. The average classification accuracies based on four different classifiers namely Nave Bayes, K-NN, SVM and BPNN, against standard database is shown in table 10. It is found that BPNN with adaptive thresholding provides better average classification accuracy consistently on all three datasets as compared to other three classifiers. Results show that the proposed feature extraction technique presented in this paper is able to give overall classification accuracy of 100% on all three datasets using BPNN as compared to other classifiers. Thus it can be inferred from the results that the proposed work provides better classification accuracy for the data sets with less number of features.

Table 1: Comparison of feature extraction time in second

|                | Colour features | Texture features | Variance-covariance features |
|----------------|-----------------|------------------|-------------------------------|
| Data set(1)    | 0.23 seconds    | 75.03 seconds    | 0.23 seconds                  |
| Data Set 2(a)  | 0.22 seconds    | 76.94 seconds    | 0.22 seconds                  |
| Data Set 2(b)  | 0.62 seconds    | 101.67 seconds   | 0.44 seconds                  |

Table 2: Classification accuracies for data set 1 using BPNN

| Data set   | 27 Texture features | 18 colour features | 45 combined features | 3 variance using RGB | 3 variance using HSV | 3 variance using HSI | 3 co-variance using RGB | 3 co-variance using HSV | 3 co-variance using HSI |
|------------|---------------------|--------------------|----------------------|----------------------|----------------------|----------------------|-------------------------|-------------------------|-------------------------|
| A          | 100                 | 100                | 100                  | 100                  | 100                  | 100                  | 100                     | 100                     | 100                     |
| B          | 97                  | 98                 | 100                  | 99                   | 100                  | 100                  | 97                      | 100                     | 100                     |
| C          | 100                 | 98                 | 100                  | 100                  | 100                  | 100                  | 99                      | 80                      | 100                     |
| D          | 100                 | 100                | 100                  | 86                   | 100                  | 100                  | 78                      | 100                     | 100                     |
Table 3: Classification accuracies for data set 2(a) using BPNN

| Data set 2(a) | 27 Texture features | 18 colour features | 45 combined features | 3 variance using RGB | 3 variance using HSV | 3 variance using HSI | 3 co-variance using RGB | 3 co-variance using HSV | 3 co-variance using HSI |
|---------------|---------------------|-------------------|---------------------|---------------------|---------------------|---------------------|------------------------|------------------------|------------------------|
| A             | 100                 | 100               | 100                 | 100                 | 100                 | 100                 | 100                    | 100                    | 100                    |
| B             | 100                 | 100               | 100                 | 100                 | 100                 | 100                 | 100                    | 100                    | 100                    |
| C             | 100                 | 100               | 100                 | 92                  | 100                 | 100                 | 100                    | 94                     | 100                    |
| D             | 100                 | 100               | 100                 | 90                  | 100                 | 100                 | 100                    | 90                     | 100                    |

Table 4: Classification accuracies for data set 2(b) using BPNN

| Data set 2(b) | 27 Texture features | 18 colour features | 45 combined features | 3 variance using RGB | 3 variance using HSV | 3 variance using HSI | 3 co-variance using RGB | 3 co-variance using HSV | 3 co-variance using HSI |
|---------------|---------------------|-------------------|---------------------|---------------------|---------------------|---------------------|------------------------|------------------------|------------------------|
| A             | 100                 | 100               | 100                 | 100                 | 100                 | 100                 | 100                    | 100                    | 100                    |
| B             | 99                  | 100               | 99                  | 100                 | 100                 | 100                 | 100                    | 100                    | 100                    |
| C             | 100                 | 100               | 100                 | 100                 | 100                 | 100                 | 100                    | 100                    | 100                    |
| D             | 99                  | 99                | 99                  | 100                 | 100                 | 100                 | 100                    | 100                    | 100                    |

Table 5: Classification accuracies for data set 1 on selected features

| Data set | 3 variance features using HSV colour space | 3 variance features using HSI colour space | 3 Co-variance features using HSI colour space |
|----------|--------------------------------------------|--------------------------------------------|-----------------------------------------------|
| A        | Bayes 100 | K-NN 100 | SVM 100 | BPNN 100 | Bayes 100 | K-NN 100 | SVM 100 | BPNN 100 | Bayes 100 | K-NN 95 | SVM 100 | BPNN 100 |
| B        | 100 | 97 | 100 | 100 | 100 | 100 | 100 | 96 | 100 | 100 |
| C        | 85 | 93 | 100 | 100 | 91 | 95 | 100 | 80 | 92 | 100 |
| D        | 100 | 94 | 100 | 100 | 94 | 100 | 100 | 93 | 100 | 100 |
Table 6: Classification accuracies for data set2 (a) on selected features

| Data Set2(a) | 3 variance features using HSV colour space | 3 variance features using HSI colour space |
|--------------|------------------------------------------|------------------------------------------|
|              | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN |
| A            | 100   | 100   | 100 | 100  | 100   | 100   | 100 | 100  | 100   | 100   | 100 | 100  |
| B            | 100   | 100   | 100 | 100  | 100   | 100   | 100 | 100  | 100   | 100   | 100 | 100  |
| C            | 100   | 98    | 100 | 100  | 100   | 98    | 100 | 100  | 100   | 100   | 100 | 100  |
| D            | 95    | 100   | 100 | 100  | 100   | 100   | 100 | 100  | 100   | 100   | 100 | 100  |

Table 7: Classification accuracies for data set2 (b) on selected features

| Data Set2(b) | 3 variance features using RGB colour space | 3 variance features using HSV colour space | 3 variance features using HSI colour space |
|--------------|------------------------------------------|------------------------------------------|------------------------------------------|
|              | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN |
| A            | 100   | 100   | 100 | 100  | 99    | 100   | 100 | 100  | 79    | 100   | 100 | 100  | 79    | 100   | 100 | 100  |
| B            | 100   | 100   | 100 | 100  | 96    | 100   | 100 | 100  | 92    | 100   | 98  | 100  | 92    | 100   | 98  | 100  |
| C            | 100   | 100   | 100 | 100  | 100   | 100   | 100 | 100  | 98    | 94    | 98  | 100  | 98    | 94    | 98  | 100  |
| D            | 100   | 100   | 100 | 100  | 80    | 100   | 100 | 100  | 100   | 94    | 100 | 100  | 100   | 94    | 100 | 100  |
Table 8: Average classification accuracies for the three data sets using variance and co-variance features

| Data Set2(b) | 3 Co-variance features using RGB colour space | 3 Co-variance features using HSV colour space | 3 Co-variance features using HSI colour space |
|--------------|---------------------------------------------|---------------------------------------------|---------------------------------------------|
|              | 3 variance features                         | 3 variance features                         | 3 Co-variance features                      |
|              | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN |
| A            | 100   | 100  | 100 | 100  | 100   | 97   | 99  | 100  | 94    | 100  | 100 | 100  |
| B            | 100   | 100  | 100 | 100  | 98    | 100  | 98  | 100  | 98    | 100  | 98  | 100  |
| C            | 100   | 100  | 100 | 100  | 100   | 100  | 99  | 100  | 96    | 100  | 98  | 100  |
| D            | 100   | 100  | 100 | 100  | 100   | 100  | 82  | 100  | 82    | 100  | 91  | 100  |

| Data | 3 variance features using HSV colour space | 3 variance features using HSI colour space | 3 Co-variance features using HSI colour space |
|------|--------------------------------------------|--------------------------------------------|-----------------------------------------------|
|      | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN |
| Set1 | 96.3  | 96   | 100 | 100  | 97.8  | 97.8 | 100 | 100  | 95    | 94   | 100 | 100  |
| Set2(a) | 98.8  | 99.5 | 100 | 100  | 99.5  | 99.5 | 100 | 100  | 96.3  | 99.5 | 100 | 100  |
| Set2(b) | 99.8  | 100  | 100 | 100  | 97.5  | 97   | 99  | 100  | 92.5  | 100  | 96.8| 100  |
Table 9: Average classification accuracies for the three data sets using colour, texture and combined features

| Data | 27 texture features | 18 colour features | 45 Combined features |
|------|------------------|------------------|---------------------|
|      | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN |
| Set1 |  97.3 |  96.5 |  98.3 |  99.3 |  99   |  99   |  99.5 |  99   |  99   |  99   |  99   |  99.5 |  99   |  100 |
| Set2(a) | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Set2(b) | 99.5 | 96.8 | 98 | 99.5 | 99.5 | 99.8 | 98 | 99.8 | 99.5 | 96.8 | 94.5 | 99.5 | 99.5 | 99.5 |

(a)
Fig 5. (a) Overall average classification accuracy for all three data sets using variance and covariance features (b) Overall average classification accuracy for all three data sets using colour, texture and combined features.

Table 10: Classification accuracies based on three standard data sets

| Class | Iris dataset | Seeds dataset | Wine dataset |
|-------|--------------|---------------|--------------|
|       | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN | Bayes | K-NN | SVM | BPNN |
| A     | 100   | 100  | 98  | 100  | 87.14 | 90   | 88.57 | 91.42 | 84.74 | 91.52 | 76.27 | 100  |
| B     | 96    | 92   | 98  | 98   | 92.85 | 92.85 | 92.85 | 100   | 97.18 | 78.87 | 100   | 95.77 |
| C     | 92    | 98   | 96  | 96   | 95.71 | 95.71 | 94.28 | 95.71 | 100   | 72.91 | 66.67 | 97.91 |
| Average | 96.67 | 97.34 | 97.34 | 91.90 | 91.90 | 95.71 | 95.71 | 93.97 | 97.89 |
VI. Conclusion

Classification of four varieties of rice using variance and covariance features are carried out successfully in this paper. This work not only reduces the feature size to just three but also improves the overall average classification accuracy. Feature extraction using variance-covariance involves simple steps and takes lesser time. It is found that adaptive thresholded BPNN is able to provide better results consistently for all the data sets discussed in this work. It is found that, nature of the input data and proper selection of training data set determines the performance of a classifier. A classifier may not always perform well if the data to be classified are quite challenging. Here, in this paper, the BPNN classifier is able to yield an average
classification accuracy of 100% using variance and co-variance features as compared to other classifiers. This shows that BPNN is the appropriate choice for classification of bulk rice grain for the three data sets presented in this paper. It can also be seen from the result, that the performance of the BPNN with adaptive thresholding, also holds good with the three standard datasets considered in this paper.

References

I. A. Douik, and M. Abdellaoui, “Cereal grain classification by optimum features and intelligent classifiers,” Int. J. of computer, communications and control, Vol.: 5, pp. 506-516, 2010 6 1

II. Agung Wibowo, Yuri Rahayu, Andi Riyanto and Tauffik Hidayatulloh, “Classification algorithm for edible mushroom identification,” International conference on Information and communications Technology (ICOIACT), Indonesia, pp. 250-253, 2018 38 2

III. Alireza Pazokia, and Zohreh Pazokia, “Classification system for rain fed wheat grain cultivars using artificial neural network,” African J. Biotechnology, Vol.: 10, Issue: 41, pp. 8031-8038, 2011 16 3

IV. Alireza Pourreza, Hamidreza Pourreza, and M.H. Hbbaspour-Fard, “Identification of nine Iranian wheat seed varieties by textural analysis with image processing,” Computers and Electronics in Agriculture. Vol.: 83, pp. 102-108, 2012 19 4

V. Alireza Sanaeifar, Adel Bakhshipour, and Miguel Dela Guardia, “Prediction of banana quality indices from colour features using support vector regression,” Talanta. Vol.: 148, pp. 54-61, 2016 29 5

VI. A.R. Pazoki, F. Farokhi, and Z. Pazoki, “Classification of rice grain varieties using two artificial neural networks (MLP and Neuro-Fuzzy),” The Journal of Animal & Plant Sciences. Vol.: 24, Issue: 1, pp. 336-343, 2014 15 6

VII. Aydin Gullu, Ozan AKI, and Erdem Ucar, “Classification of rice grain using image processing and machine learning techniques,” International Scientific Conference, pp. 352-354, 2015 22 7

VIII. B.S. Anami, D.G. Savakar, and Aziz Makandar, “A neural network model for classification of Bulk grain samples based on colour and texture,” Proceeding of International conference on cognition and recognition, pp. 359-368, 2005 17 8

IX. D.K. Srivastava, and Lekha Bhambhu, “Data Classification Using Support Vector Machine,” Journal of Theoretical and Applied Information Technology, Vol.: 12, Issue: 1, pp. 1-7, 2010 23 9

X. F. Guevara-Hernandez, and J. Gonez-Gil, “A machine vision system for classification of wheat and barley grain kernels,” Spanish Journal of Agricultural Research. Vol.: 9, Issue: 3, pp. 672-680, 2011 24 10
XI. Federico Marini, Remo Bucci, and Antonio L. Magri, “Classification of 6 durum wheat cultivars from Sicily (Italy) using artificial neural network,” Chemometrics and intelligent laboratory systems, Vol.: 90, pp.1-7, 2007 7 11

XII. Harpreet Kaur, and Baljit Singh, “Classification and grading of rice using multi-class SVM,” International Journal of scientific and research publication, Vol.: 3, Issue: 4, pp. 1-5, 2013 25 12

XIII. H.K. Mebatsion, J.Paliwal, and D.S. Jayas, “Automatic classification of non-touching cereal grain in digital image using limited morphological and colour features,” Computers and electronics in Agriculture. Vol.: 90, pp. 99-105, 2013 3 13

XIV. Ian C. Navotas, Charisse Nadine V. Santos, Earl John M. Balderrama, Francia Emmanuelle B. Candido, Aloysius John E. Villacanas, and Jessica S. Velasco, “Fish identification and freshness classification through image processing using artificial neural network,” ARPN Journal of Engineering and Applied Sciences, Vol.:13, Issue: 18, pp. 4912-4922, 2018 46 14

XV. Iman Golpour, Jafar Amir Parian, and Reza Amir Chayjan, “Identification and classification of bulk paddy, brown, and white rice cultivars with colour features extraction using image analysis and neural network. Czech J. Food Sci. Vol.: 32, Issue: 3, pp. 280-287, 2014 26 15

XVI. Irena Orina, Marena Manley, and Paul J. Williams, “Non-destructive technique for detection of fungal infection in cereal grain”, Food Research International. Vol.: 100, pp. 74-86, 2017 32 16

XVII. Irmgard Hein, Aifonso Rojas-Dominguez, Manuel Ornelas, Giulia D’Ercole, and Lisa Peloschek, “Automatic classification of archaeological ceramic materials by means of texture measures,” Journal of Archaeological Science Report, Vol.: 21, pp. 921-928, 2018 44 17

XVIII. Ji Sang Bae, Sang-Ho Lee, Kang Sun Choi, and Jonk ok kim, “Robust skin roughness estimation based on co-occurrence matrix,” J. Vis. Commun. Image R., Vol.: 46, pp. 13-22, 2017 33 18

XIX. J. Paliwal, N.S. Visen, and D.S. Jayas, “Evaluation of neural network architecture for cereal grain classification using morphological features.” J. agric. Engg Res., Vol.: 79, Issue: 4, pp. 361-370, 2001 4 19

XX. J. Paliwal, N.S. Visen, and D.S. Jayas, “Cereal grain and dockage identification using machine Vision,” Bio-system Engineering. Vol.: 85, Issue: 1, pp. 51-57, 2003 14 20

XXI. Kamil Dimililer and Ehsan Kiani, “Application of Back Propagation Neural Networks on Maize plant detection”. Procedia Computer Science, 9th International Conference on theory and applications of soft computing, computing with words and perceptron, ICSCCW, Hungary, pp. 376-381, 2017 34 21

XXII. Kivan Kılıc, Ismail Hakki Boyaci, and Hamit KoKsel, “A classification system for beans using computer vision system and artificial neural networks,” Journal of Food Engineering, Vol.: 78, pp. 897-904, 2007 8 22
XXIII. K. Neelamma Patil, S. Virendra, and Malemath, “Colour and texture based identification and classification of food grains using different colour models and Haralick features,” International journal of Computer Science and Engineering. Vol.: 3, pp. 3669-3679, 2011 21 23

XXIV. Kusworo Adi, Catur Edi Widodo, Aris Puji Widodo, Rahmat Gernowo, Adi Pamungkas, and Rizky Ayom Syifa, “Detection lungs cancer using Gray level co-occurrence matrix (GLCM) and Back propagation neural network classification,” Journal of Engineering Science and Technology Review, Vol.:11, Issue: 2, pp. 8-12, 2018 45 24

XXV. Lin Mar Oo and Nay Zar Aung, “A simple and efficient method for automatic strawberry shape and size estimation and classification,” Biosystem Engineering, Vol.: 170, pp. 96-107, 2018 39 25

XXVI. LIU Zhao-yan, CHENG Fang, and YING Yi-bin, “Identification of rice seed varieties using neural network,” Journal of Zhejiang University SCIENSE. Vol.: 6B, Issue: 11, pp.1095-1100, 2005 9 26

XXVII. Malay Kishore Dutta, Ashish Issac, Navroj Minhas, and Biplab Sarker, “Image processing based method to assess fish quality and freshness,” Journal of Food Engineering. Vol.: 177, pp. 50-58, 2016 30 27

XXVIII. Malgorzata Charytanowicz, PiotrKulezycki and piotr A. Kowalski, “An evaluation of utilized geometric features for wheat grain classification using X-ray image,” Computers and Electronics in agriculture. Vol.: 144, pp. 260-268, 2018 40 28

XXIX. Muhammad Tahir, “Pattern analysis of protein image from fluorescence microscopy using GLCM,” Journal of King Saud University Science, Vol.: 30, pp. 29-40, 2018 41 29

XXX. N.S. Visen, J. Paliwal, D.S. Jayas, “Image analysis of bulk grain samples using neural network,” Canadian Biosystem Engineering. Vol.: 46, pp. 7.11-7.15, 2004 18 30

XXXI. P. Vithu, and J.A. Moses, “Machine vision system for food grain quality evaluation: A review,” Trends in food Science and Technology. Vol.: 56, pp. 13-20, 2016 31 31

XXXII. Rafael C Gonzalez and Richard E Woods, “Digital Image Processing,” New Delhi, Pearson Prentice Hall (2009). 2 32

XXXIII. R. Choudhary, J. Paliwal, and D.S. Jayas, “Classification of cereal grain using wavelet, morphological, colour and texture features of non-touching kernel,” Biosystem Engineering, Vol.: 99, pp. 330-337, 2008 5 33

XXXIV. Sabiq Adzhani Hamnam, Tito Waluyo Purboyo, and Randy Erfa Saputra, “Cotton texture segmentation based on image texture analysis using gray level run length and Euclidian distance,” Journal of theoretical and applied information technology. Vol.: 95, Issue: 24, pp. 6915-6923, 2017 35 34

XXXV. Saurabh Agrawal, N.K. Verma, & Prateek Tamrakar, “Content based colour image classification using SVM,” Eight International conferences on information technology: New generation (2011), pp. 1090-1094, 2011 27 35

XXXVI. Silvia Grassi, Ernestina Casiraghi, and Cristina Alamprese, “Fish fillet authentication by image analysis,” Journal of food Engineering, Vol.: 234, pp. 16-23, 2018 43 36
XXXVII. Sitt Wetenriajeng, Ansar Suyuti, Intan Sari arena and Ingrid Nurtanio, “Classification of Passion fruit’s ripeness using K-mean clustering and Artificial neural network,” International conference on Information and communications Technology (ICOIACT), Indonesia, pp. 304-309, 2018

XXXVIII. S. Jayaraman, S. Esakkirajan, and T. Veerakumar, “Digital Image Processing,” New Delhi, Tata McGraw Hill Education (2009).

XXXIX. S. Majundar, and D.S. Jayas, “Classification of bulk samples of cereal grain using machine vision,” J. Agric. Engng Res. Vol.: 73, pp. 35-47, 1999

XL. S. Majundar, and D.S. Jayas, “Classification of cereal grain using machine vision. I. Morphology model,” Transaction of the ASAE, Vol.: 43, Issue: 6, pp.1669-1675, 2000

XLI. S. Majundar, and D.S Jayas, “Classification of cereal grain using machine vision. II. Colour model,” Transaction of the ASAE. Vol.: 43, Issue: 6, pp.1677-1680, 2000

XLII. S. Majundar, and D.S. Jayas, “Classification of cereal grain using machine vision. III. Texture Model,” Transaction of the ASAE. Vol.: 43, Issue: 6, pp.1681-1687, 2000

XLIII. S. Majundar, and D.S. Jayas, “Classification of cereal grain using machine vision. IV. Combined morphology, colour and texture model,” Transaction of the ASAE. Vol.: 43, Issue: 6, pp.1689-1694, 2000

XLIV. Suharjito, Bahtiar Imran and Abba Suganda Girsang, “Family relationship identification by using Extract Features of Gray Level Co-occurrence Matrix (GLCM) Based on Parents and Children Fingerprint,” International Journal of Electrical and Computer Engineering, Vol.: 7, Issue: 5, pp. 2738-2745, 2017

XLV. Wan Nur Hafsha Wan Kairuddin and Wan Mahani Hafizah Wan Mahmud, “Texture feature analysis for different resolution level of kidney ultrasound images,” International Research and Innovation Submit (IRIS2017). IOP Conf. Series: Material Science and Engineering 226, pp. 1-9, 2017

XLVI. Yudong Zhang, Shuihua Wang, and Genlin Ji, “Fruit classification using computer vision and feed forward neural network,” Journal of Food Engineering. Vol.: 143, pp. 167-177, 2014