# Color and texture features for classification of bulk grains using Artificial Neural Network

K s h .Robert Singh
*Assistant Professor, Department of Electrical Engineering*
*Mizoram University*
*Aizawl-796004, India*

***Abstract:-*****This paper describes the technique for automatic recognition and classification of different bulk rice grain samples using neural network classifier. The Red Green Blue (RGB), Hue Saturation Intensity (HSI) and Hue Saturation Value (HSV) color models of the image were considered for extracting 18 color features. The classification was carried out using color and texture features separately. The color image was converted to gray scale image and the Gray Level Co-occurrence Matrixes (GLCM) for four different directions was calculated. A total of eight texture features were calculated from the Co-occurrence matrices. Back Propagation Neural Network (BPNN) is used for the classification process. The classification accuracy with color features and texture features were compared. Result shows that the classification base on texture features outperform the color feature based classification even with lesser number of features. It is found that Back Propagation Neural network was able to classify four varieties of rice with 100% accuracy using texture features.**

**Keywords: Co-occurrence matrix, color and texture features, Back Propagation Neural Network.**

## I. INTRODUCTION

Image processing system has wide application in handling, grading of agricultural products, classification of plants, recognition of leaves, gradation of roses, and diagnosis of plant diseases etc. using an artificial neural network approach. Manual inspection of grain samples were quite tedious and time consuming. Handling of grains requires information of grain types and grain quality at several stages before the course of operation is carried out. Image processing and computer vision system became an alternative to manual inspection of grain samples for characteristic properties and the amount of foreign material.

The performance of a grain inspector (the one who grades the grains) is seriously affected by his/her physical condition such as fatigue and eyesight, mental state caused by biases, work pressure, and working conditions such as improper lighting, climate, etc. Owing to these facts, it is better; this task is carried out automatically. A methodology for the classification and gradation of different grains (for a single grain kernel) such as groundnut, Bengal gram, wheat etc. is described [1] [2] [7]. Much of the published research were carried out using morphological features to classify different grain species, classes, varieties, damaged grains, and an impurity, using statistical pattern recognition techniques.[10] [11] Some researchers have tried to use color features for grain identification. Works had also been done to incorporate textural features for classification purposes. Efforts have also been made to integrate all these features in terms of a single classification vector for grain kernel identification [4] [11] [12].

Most of the published research mainly focuses on identification and classification of grain kernels by placing grain kernels in a non-touching fashion. Such a process is comparatively difficult, time consuming and requires cumbersome setup. In order to perform the task in real-time the systems generally require a device to present kernels in a non-touching manner, an independent conveyor belt assembly, and the typical imaging devices. The algorithms for classification of grains base on grain kernels require pre-processing operations such as segmentation, background removal, and object extraction, which are some of the most time-consuming operations. On the other hand, if the process for identification and classification of cereal grain has to be carried out using images of bulk samples, then many of the requirements of the previously described system become redundant. Moreover, an image of a bulk sample does not contain individual objects in it, so it does not need to be pre-processed for background removal and object extraction.

This paper describes the classification of bulk grain samples using color and texture features separately. Previous research suggests that a back propagation neural network is best suited for classification of cereal grains [1] [10]. Based on this, the classification in this paper has been carried out using BPNN.

The process in this paper involves extracting the 18 color features and 8 GLCM base texture features from the bulk grain images and finally developing a suitable Back Propagation Neural Network model to recognize the different types of grain images. Images of different grains were obtained using digital camera. Color and texture features were extracted using image-processing techniques. These features were used to train the Neural Network-based classifier. The developed neural network model was then tested for classification of different bulk grain images.

In training phase the patterns which are nothing but set of features are stored in the form of weights in the network as a knowledge base with respect to their corresponding target. The strength of classification is tested by applying a test input. As soon as the test pattern is feed to the network will try to converge to the specified target.

## II. FEATURES EXTRACTION

The feature extraction algorithm development is done on a computer. The algorithm extracted 18 color features and 8 textural features from bulk sample images [1] [2] [7].

### *2.1 Sample images*

A total of 400 samples were taken for four varieties of rice (hundred samples for each rice grain type). Out of hundred sample images 50 images were used for training phase so, a total of 200 images for all four varieties of grain were used for training phase. The remaining 200 images were reserved for testing. Four varieties of bulk grain samples is shown in fig1.


Figure 1: Bulk rice image

### *2.2 Color Feature Extraction*

The original 24 -bit color images are of size M*N*3 where M and N are the height and width of image respectively and 3 indicates the three 8-bit color components of the original images, viz. Red(R), Green (G), and Blue (B). From the original images, RGB components were separated and the following components were extracted; Hue (H), Saturation (S) Intensity (I) and Value (V). Mean, variance and range of the RGB plains and HIS plains were calculated which constitutes the 18 color features. Similarly another 18 color features were also extracted from RGB plains and HSV plains. The following equations represent the conversion process [8] [9].

RGB to HSI:

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

Where,

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

$$S = 1 - \frac{3}{(R+G+B)}\left\{\min(R,G,B)\right\} \quad (2)$$

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

RGB to HSV:

The expression for Hue is the same as in Equation 1.

$$\text{Saturation} = \begin{cases} 1-\frac{m}{M} & \text{if } M > 0 \\ 0 & \text{if } M = 0 \end{cases} \quad (4)$$

Where, M= max{R, G, B}
m= min{R, G, B}

$$\text{Value} = M/255 \quad (5)$$

*2.3 Texture Feature Extraction*

Texture is contiguous set of pixels with some tonal and/or regional property. Texture can be characterized by tone, intensity property texels, structure and spatial relationship of texels. It provides the information about the variation in the intensity of a surface by quantifying properties such as smoothness, coarseness, and regularity [1] [2] [7]. The most widely accepted models that describe texture features, are those that use the co -occurrence and run-length matrices [2]. In this study, we used the gray level co -occurrence matrix at level 16 and 32 (an integer specifying the number of gray levels to use when scaling the gray scale value of the input gray scale image). In order to reduce the computation time required for the calculation of GLCM, the above two levels were chosen which will results to 4 GLCM with size 16x16 and other 4 GLCM with size 32x32. The co-occurrence matrix method of texture description is based on the repeated occurrence of some gray-level configuration in the texture. This configuration varies rapidly with distance in fine textures and slowly in coarse textures. Suppose the part of a textured image to be analyzed is an M * N rectangular window. An occurrence of some gray-level configuration may be described by a matrix of relative frequencies $P_{f,d}(x, y)$, describing how frequently two pixels with gray -levels *x, y* appear in the window separated by a distance *d* in the direction *f. A* Gray Level Co-occurrence Matrix (GLCM), for four different values of direction 'f' ($0^o$, $45^o$, $90^o$ and $135^o$) and distance (d=1) were calculated from the gray scale rice grain image. GLCM properties namely energy and homogeneity were considered for texture feature extraction and were calculated from each of the four GLCM matrices. Energy describes the uniformity of gray levels in the image. It is given by summation of the square elements in the GLCM. Homogeneity provides the information of closeness of the distribution of elements in the GLCM to GLCM diagonal.

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

$$P_{45,\,d}(x, y) = \sum_{p=n}^{1}\sum_{q=1}^{m}\begin{cases} 1 & \text{if } f(p.q)=x \text{ and if } (p-\Delta x,q+\Delta y)=y \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$P_{90,\,d}(x, y) = \sum_{p=n}^{1}\sum_{q=1}^{m}\begin{cases} 1 & \text{if } f(p.q)=x \text{ and if } (p-\Delta x,q)=y \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$P_{135,\,d}(x, y) = \sum_{p=n}^{1}\sum_{q=m}^{1}\begin{cases} 1 & \text{if } f(p.q)=x \text{ and if } (p-\Delta x,q-\Delta y)=y \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$\text{Energy} = \sum_{x,y} P^2(x, y)$$
(10)

$$\text{Homogeneity} = \sum_{x,y}\frac{P(x, y)}{1+|x-y|} \tag{11}$$

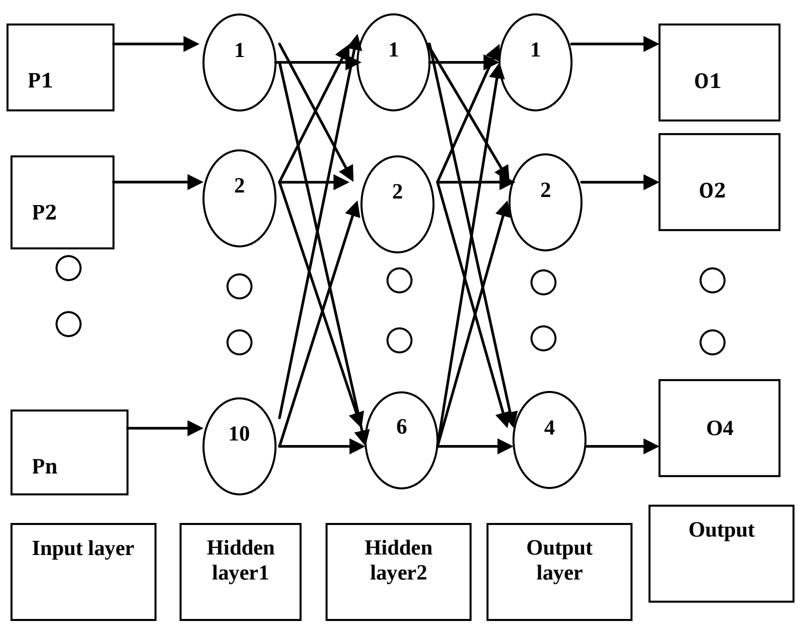


Figure 2: Neural network model for classification

## III. CLASSIFICATION OF GRAINS

This section explains the ANN architecture, classification models, training, testing, & validation of neural network. ANN's are physical cellular systems, which can acquire, store
and utilize experimental knowledge. Neural Networks have found applications in pattern classification, image processing, face and character recognition etc [1] [2] [3] [4]. Data base of features were created for each category of rice using 400 images (100 images for each rice type). The classification was then performed for 4 different types of feature vectors, 18 color features from combined RGB and HIS image plains, another 18 color features from combined RGB and HSV image plains. Eight texture features from gray scale image, one at level 16 and another at level 32.

*3.1 Neural network model (classifier)*

This paper describes the designed and implemented of BPNN using Matlab 2010a software. It has been claimed in [1] [10] 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 typical neural network model developed to classify the grains is shown in Fig.2.

The classification process involves the following steps:

1. Assemble the training data.
2. Create the network.
3. Train the network.
4. Test the network response to new input.

The number of input neurons is n, which is equal to the dimensionality of the input pattern vectors. The numbers of hidden neurons were calculated using the relation given in [1].

$$N = \frac{I - O}{2} + Y^{0.5} \qquad (12)$$

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

## IV. RESULTS AND DISCUSSION

The classification accuracies for different features vectors were presented in table1. The simulation results also provide the performance plot for training, testing and validation. Blue line in the performance plot indicates the decreasing error on the training data set, green line indicates the validation error and the training stops when the validation error stops, red line shows error on the test data. The performance plot of 8 GLCM features at level 16 for type 1 rice grain is shown in fig 3. The classification accuracies for 4 different varieties of bulk rice grains with different features vectors were presented in fig 4.

Table 1: Classification accuracy for different features

| **Features vector** | **% Accuracies** | | | |
|---|---|---|---|---|
| | **Type 1** | **Type2** | **Type3** | **Type4** |
| **18 color features RGB&HSI** | **100** | **100** | **100** | **100** |
| **18 color features RGB&HSV** | **100** | **100** | **100** | **100** |
| **9 color features RGB&HSI** | **100** | **100** | **98** | **100** |
| **9 color features RGB&HSV** | **100** | **100** | **100** | **100** |
| **8 GLCM at level 16** | **100** | **99** | **100** | **100** |
| **8 GLCM at level 16** | **100** | **100** | **100** | **100** |

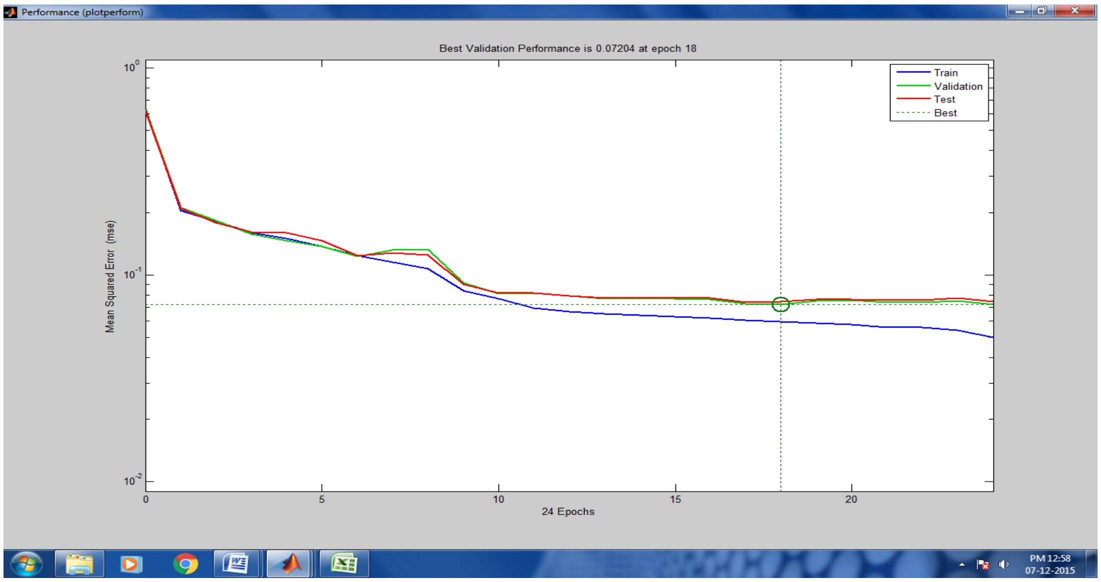


Figure 3: Performance plot of training, testing and validation

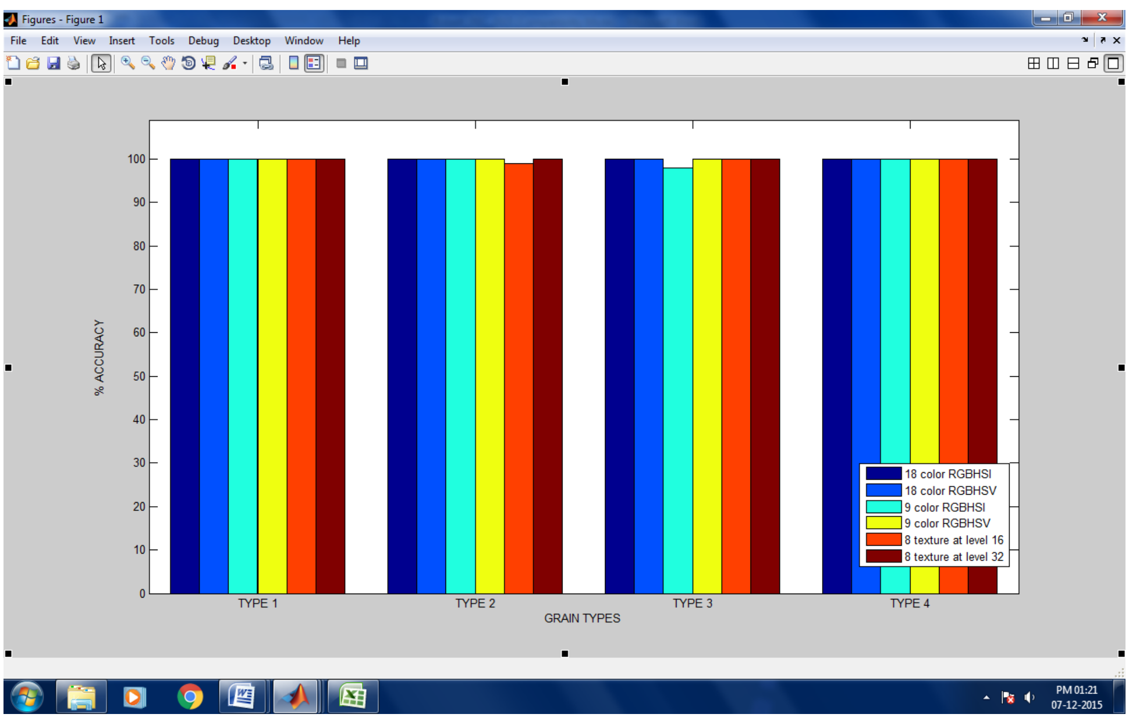


Figure 4: Comparison of classification accuracies for different features

It is found that the classification accuracies with 18 color features of RGBHSI combinations is equally efficient with that of RGBHSV combinations for the classification of 4 varieties of rice grain however, the classification accuracy of RGBHSV with reduced features (feature reduced to 9 while other 9 redundant features were discarded) prove to be more efficient than that of the reduced features with RGBHSI combination. The result also shows that the texture feature using 8 GLCM features at level 32 is able to classify all 4 varieties of rice grains with 100% accuracy as compare to GLCM at level 16. It is evident that the overall classification accuracy of 100% is being achieved using texture base classification with lesser number of features as compare to color features.

## V. CONCLUSION

It is evident that the Image processing systems faithfully classify the four varieties of rice grains. Such a computer vision system can replace the human inspection system because of their high speed, precision and indefatigable operation. Image acquisition, processing and pattern classification using Artificial Neural Network can be coupled together and used in a machine vision system for automatic recognition and classification of different grain samples. Bulk grain samples make it easy to arrange and classify with minimum image processing techniques. The consistency of the results of this neural network classifier indicates that they are an apt choice to classify various agricultural products. This paper suggests that texture features are more suitable for identification and classification of bulk grain samples than that of color features.

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