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CLASSIFICATION OF RICE USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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ABSTRACT
This paper describes the technique for automatic recognition and classification of different 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. Convolutional Neural Network (CNN) 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 Convolutional Neural network was able to classify two varieties of rice with 100% accuracy using texture features and the edge detection with Sobel and Canny edge detection of the fiber features in the food grain.
Keywords: Feature extraction, Food grain samples, Co-occurrence matrix, Color and Texture Features, Convolutional Neural Network.

1. 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

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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.

2. Feature Extraction:

The feature extraction algorithm development is done on a computer. The algorithm extracted 18 color features, 27 GLCM textural features from individual sample images and Different Edge Detection Techniques like Sobel and Canny edge Detections from the sample images.

2.1 Sample images:

A total of 60000 samples were taken for two varieties of rice. Out of Thousand sample images 30000 images were used for training phase so, a total of 15000 images for all two varieties of grain were used for training phase. The remaining 15000 images were reserved for testing. Two varieties of Individual grain samples are shown in fig1.

Figure 1: 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:

$$H = \begin{cases} \theta & if\ B \leq G \\ 360 - \theta & if\ B > G \end{cases}$$

Where,

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

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

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

RGB to HSV:

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

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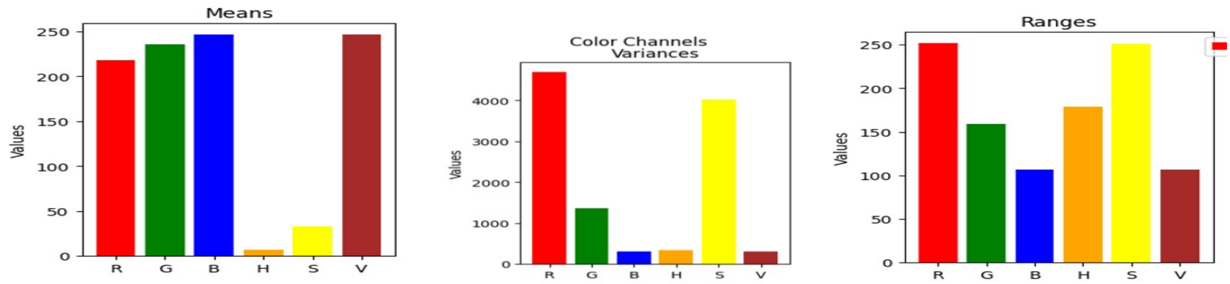
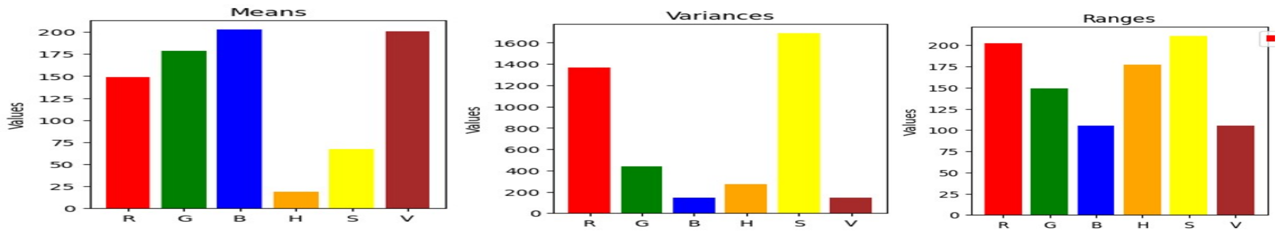
$$Saturation = \begin{Bmatrix} 1 - \frac{m}{M} & if\ M > 0 \\ 0 & if\ M = 0 \end{Bmatrix}$$

Where M = max {R, G, B}
m = min {R, G, B}
Value = M/255

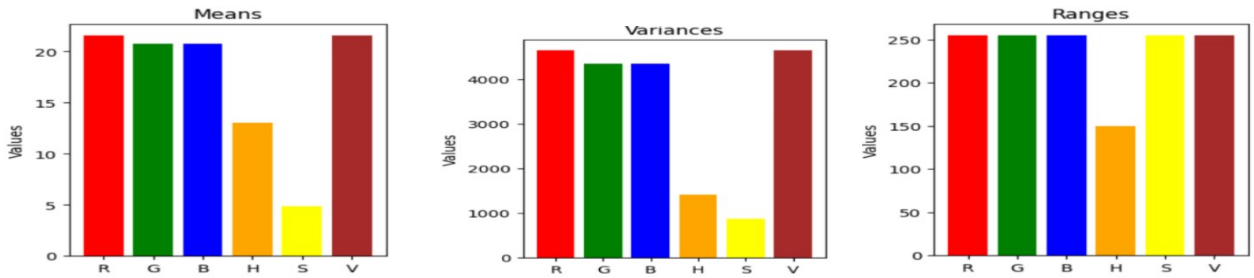
a. For Paddy:



b. For Unpolished:



c. For Polished:



Sl. No	Features	Sl. No		Sl. No	Features
1	Red Mean	7	Blue Mean	13	Saturation mean
2	Red Variance	8	Blue Variance	14	Saturation Variance
3	Red range	9	Blue range	15	Saturation range
4	Green Mean	10	Hue Mean	16	Intensity Mean
5	Green Variance	11	Hue Variance	17	Intensity Variance
6	Green range	12	Green range	18	Intensity Range

Table 1: Color Features

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

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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 analysed is an M * N rectangular window. An occurrence of some Gray-level configuration may be described by a matrix of relative frequencies Pf,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' (0o, 45o, 90 and 135) 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.

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

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

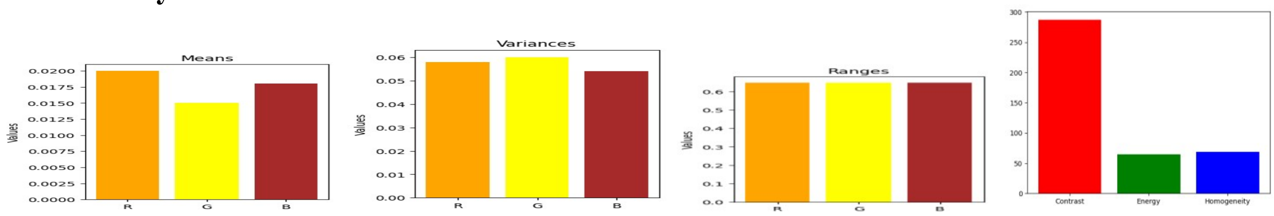
$$P_{45,\ d}(X,Y) = \sum_{p=n}^{1}\sum_{q=1}^{m}\begin{cases}1 & if\ f(p,q) = x\ and\ if(p-\Delta x, q+\Delta y) = y\\ 0 & otherwise\end{cases}$$

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

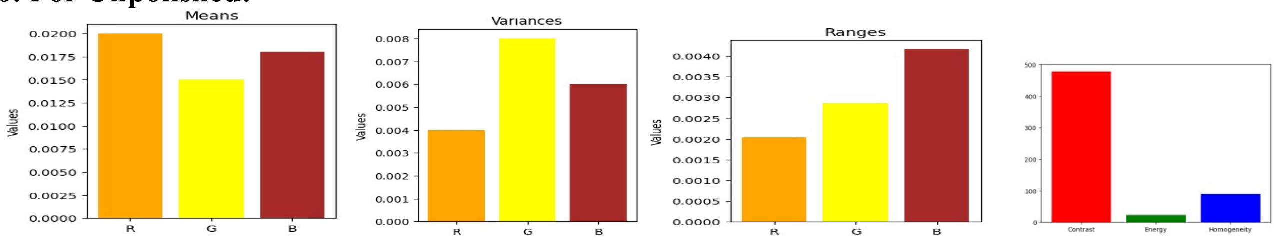
$$Energy = \sum_{x,y} P^2(X,Y)$$

$$Homogeneity = \sum_{x,\ y}\frac{P(X,Y)}{1+|X-Y|}$$

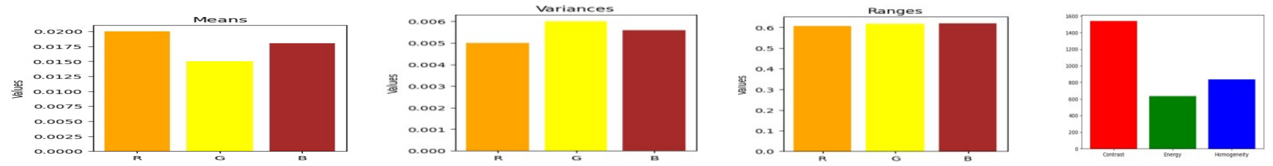
a. For Paddy:



b. For Unpolished:



c. For Polished:



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3. TEXTURE GRADING:

Texture grading levels can play a crucial role in assessing the quality and processing suitability of rice grains. The texture of rice grains can vary depending on factors such as the presence of bran, the level of polishing, and the overall surface smoothness. By analyzing the texture characteristics of rice grains, it is possible to distinguish between different grades, such as paddy, unpolished, and polished rice. Here's an overview of the texture grading levels associated with these rice grain types:

3.1 Grading Level 1:

Polished rice, also called white rice, has undergone additional processing to remove the bran layer, resulting in a smoother and more uniform texture compared to unpolished rice. The texture of polished rice is characterized by a glossy and translucent appearance. The surface of polished rice grains is generally smooth and even, without the presence of bran particles. Texture grading of polished rice focuses on evaluating the level of smoothness and uniformity across the grain surface.

3.2 Grading Level 2:

Unpolished rice, also known as brown rice, has had the outer husk removed but retains the bran layer. The texture of unpolished rice is characterized by a slightly rough and uneven surface due to the presence of the bran. The bran layer contains important nutrients and dietary fiber. Texture grading of unpolished rice involves assessing the degree of bran adherence and examining the overall surface texture for any irregularities or defects.

3.3 Grading Level 3:

Paddy rice refers to rice grains that still have their husks intact. The texture of paddy rice is typically rough and uneven due to the presence of the husk, which gives it a coarse and grainy appearance. The husk provides protection to the rice grain during storage and transportation, but it needs to be removed before the grain can be consumed. Texture analysis of paddy rice focuses on evaluating the roughness and irregularity of the husk surface.

Texture grading of rice grains can be performed using various techniques, including visual inspection, image analysis, and sensory evaluation. Image analysis techniques leverage computer vision algorithms to extract texture features from rice grain images and classify them into different grading levels. These features can include statistical measures of surface roughness, grain uniformity, and the presence of bran particles.

It is important to note that specific grading criteria and standards may vary across regions and markets. Therefore, it is essential to consult the relevant regulatory authorities or industry guidelines to understand the specific texture grading levels and requirements for paddy, unpolished, and polished rice in a particular context.

3.4 Edge-based segmentation method for feature Extraction:

The common feature of the fiber for all Rice grains is that the edge of the Rice grain is obvious. Based on the character, we proposed an enhanced edge detection method to complete the feature extraction the fiber of the Rice grains. The algorithm, which selectively retains the boundary points based on a Sobel operator, is the following.

3.4.1 Canny Edge Detection:

The Canny edge detection algorithm works by first smoothing the input image using a Gaussian filter to remove any noise. Then, the gradient magnitude and direction are calculated at each pixel in the smoothed image. The gradient direction is rounded to one of four angles (0°, 45°, 90°, or 135°) to reduce the number of possible edge orientations.

(1) Canny edge detector is an optimal detector which gives optimal filtered images.

(2) Canny edge detector also contains weak edges which are connected to strong edges.

The Canny edge detection algorithm has several advantages over other edge detection algorithms, such as the ability to accurately detect edges with low contrast or noisy images, and the ability to detect edges with varying widths and orientations

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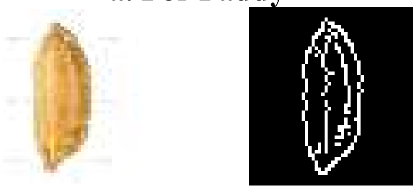
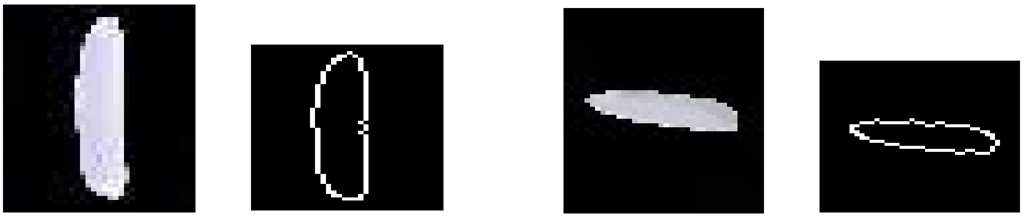
a. For Paddy



b. For Unpolished:

c. For Polished:



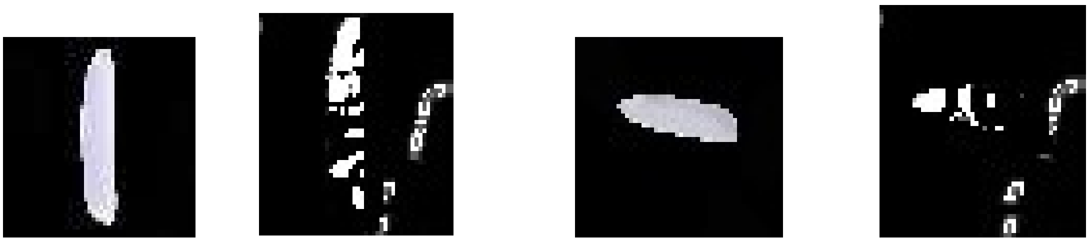
3.4.2 Sobel Edge Detection:

1) A Sobel operator was employed to obtain the boundary image; the pixel value of the border points was 1, and pixel value of the background was 0.
2) Series of gradient Magnitudes are created using a simple convolution kernel.
3) After expansion, thinning, removing isolated and bright points, acquisition of the Rice edge image is completed.

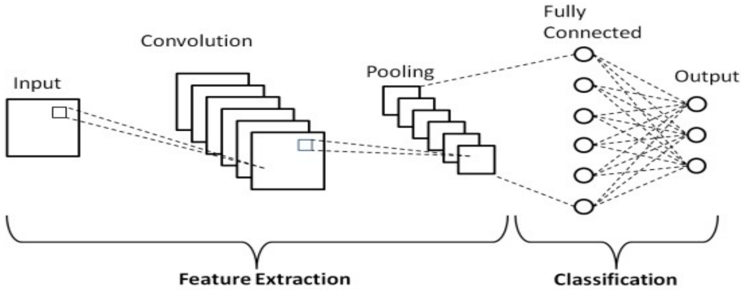
a. For Paddy:

b. For Unpolished:

c. For Polished:



4. CLASSIFICATION OF GRAINS:



This section explains the CNN architecture, classification models, training, testing, & validation of neural network. 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 30000 images (15000 images for each rice type). Eight texture features from gray scale image.

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1. It consists of three convolutional layers. The first convolution layer uses 16 convolution filters with a filter size of 3x3, kernel regularise and bias regularise of 0.05.
2. In the image, a certain collection of pixels may represent an edge in one image, some may represent the shadow of an image or some other pattern.
3. It also uses random_uniform, which is a kernel initializer. It is used to initialize the neural network with some weights and then update them to better values for every iteration.
4. Random_uniform is an initializer that generates tensors with a uniform distribution.
5. Regularise is used to add penalties on the layer while optimizing. These penalties are used in the loss function in which the network optimizes.
6. No padding is used so the input and output tensors are of the same shape. The input image size is 224x224x3.
7. Then before giving output tensor to max-pooling layer batch normalization is applied at each convolution layer which ensures that the mean activation is nearer to zero and the activation standard deviation nearer to 1.
8. After normalizing RELU an activation function is used at every convolution. The rectified linear activation function (RELU) is a linear function.
9. The output of each convolutional layer given as input to the max-pooling layer with the pool size of 2x2.
10. This layer reduces number the parameters by down-sampling. Thus, it reduces the amount of memory and time required for computation.
11. The finally a dropout of 0.5 is used for faster computation at each convolution. The 2nd convolution layer uses 16 convolution filters with 5×5 kernel size and the third convolution layer use 16 convolution filters with 7x7 kernel size. Finally, we use a fully connected layer.
12. Here dense layer is used. Before using dense we have to flatten the feature map of the third convolution. In our model, the loss function used is categorical cross-entropy and Adam optimizer with a learning rate of 0.0001. In the proposed CNN model architecture the classification process involves the following steps:

1. Assemble the training data.
2. Create the network (CNN network).
3. Train the network.

a) Feature Extraction -input, convolution, pooling
b) Classification- fully connected and Output

3. Test the network response to new input.

5. RESULT AND DISCUSSION:

The classification accuracies for 2 different varieties of individual rice grains with different features vectors were presented. 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 2 varieties of rice grain however, the classification accuracy of RGBHSV with reduced features prove to be more efficient than that of the reduced features with RGBHSI combination. The result also shows that the texture feature using 27 GLCM features is able to classify all 2 varieties of rice grains with 100% accuracy as compare to GLCM. 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.

6. CONCLUSION

It is evident that the Image processing systems faithfully classify the two 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 Convolutional Neural Network can be coupled together and used in a machine vision system for automatic recognition and classification of different grain samples. Bulk grain

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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.

Variations in image sizes also affect the recognition and classification accuracies. Hence, it is inferred that any variation in size of image and the distance of acquisition has impact on accuracy of recognition of food grain samples. In this case, reduction in accuracy observed matches with the human vision system too. Furthermore, image size plays an important role in recognition and classification process.

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