Color and Texture Based Identification and Classification of food Grains using different Color Models and Haralick features

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***Abstract*— This paper presents the study on identification and classification of food grains using different color models such as L*a*b, HSV, HSI and YCbCr by combining color and texture features without performing preprocessing. The K-NN and minimum distance classifier are used to identify and classify the different types of food grains using local and global features. Texture and color features are the important features used in the classification of different objects. The local features like Haralick features are computed from co-occurrence matrix as texture features and global features from cumulative histogram are computed along with color features. The experiment was carried out on different food grains classes. The non-uniformity of RGB color space is eliminated by L*a*b, HSV, HSI and YCbCr color space. The correct classification result achieved for different color models is quite good.**

Keywords- Feature Extraction; co-occurrence matrix; texture information; Global Features; cumulative histogram; RGB, L*a*b, HSV, HSI and YCbCr color model.

I. Introduction

In the present grain-handling scenario, grain type and quality are identified manually by visual inspection. Human beings recognize fruits, grains, flowers and many other agriculture and horticulture produce based on shape, size, color and patterns. At present, the produce and their quality are rapidly assessed through visual inspection by human inspectors. This evaluation process is however, tedious and time consuming. Hence, these tasks require automation and develop imaging systems that can be helpful to identify different food grain images, rectify it & then being analyzed. The decision-making capabilities of human-inspectors are subjected to external influences such as fatigue, vengeance, bias etc. The farmers are very much affected by this manual activity in terms of returns for their crop. Hence, these tasks require automation, so as to have a computer vision system as an alternative to this manual practice.

Machine Vision Systems are successfully used for Identification and Classification of plants, leaves, flowers, bulk grain samples [9-13]. Color and texture information have been a great help in identifying objects from many years. In order to perform this task of pattern recognition by machines, considerable design effort is necessary. We have carried out literature survey to explore usage of these methods in different fields. Several researchers have reported that computer vision systems are more accurate in classification and interpretation of the images, as carried out by human beings in the real world.

In the early days of machine vision application to grain quality evaluation, Lai et al. suggested some pattern recognition techniques for identifying and classifying cereal grains [1]. Some investigations were carried out using color features for classification of different cereal grains and their varieties for correlating vitreosity and grain hardness of Canada Western Amber Durum (CWAD) wheat [2-4]. Huang et al. proposed a method of identification based on Bayes decision theory to classify rice variety using color features and shape features with 88.3% accuracy [5]. Majumdar and Jayas developed classification models by combining two or three features sets (morphological, color, textural) to classify individual kernels of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oat, and rye [6-9]. Neelamma et al. have performed classification on food grains using HSI color model and achieved 83.66% using 50% training set with 512x512 and 256x256 block size [21].The Sanjivini et al., have carried out the experiment on rice grains and performed pre-processing and segmentation process which is tedious [10].

Neuman M., et al. have developed a back propagation neural network-based classifier to identify color images of bulk grain samples of five grain types, namely barley, oats, rye, wheat, and durum wheat [4]. Classification accuracies around 98% are obtained for the considered grain types using 150 color and textural features together. Anami B.S, et al. have developed a Neural network approach to classify single grain kernel of different grains like wheat, maize, groundnut, redgram, greengram and blackgram based on color, area covered, height and width [12]. The minimum and maximum classification accuracies are 80% and 90% respectively.

Most of the published research work mainly focuses on identification of grains such as wheat, barley, oats and the like using large number of features. To the best of our knowledge, little or no work on recognition and classification of food grain image samples such as corn, horse gram, peas, pearl millet and bengal gram in the Indian context is cited in the literature. Hence, it is the motivation for the present work on images of agriculture produce. We have performed experiment on 10 different classed such as maize, wheat, corn, cow peas, greengram, horsegram, bengalgram, pearl millet, redgram and peas.

The rest of this paper is organized as follows: section 2 presents system overview and proposed work. Section 3 describes features extraction. Section 4 presents experimental set up. Section 5 discusses the experimental results. Finally, section 6 introduces the conclusions of this work.

II. THE SYSTEM OVERVIEW AND PROPOSED WORK

The robustness of the system depends on the features extracted. In this paper, the experiment was carried out on 10 different classes of food grains. The process of classification is performed in two phases; the first one is the computation of features and second is the classification of food grains with the help of extracted features using suitable classifiers. The original images used for the experimentation are captured under natural light and are resized to 1024x1024. The K-NN and minimum distance classifiers are used for classification using extracted global, local and color features.

A. Color Model Conversion

Color is the most vital visual feature for humans. By color representation we mean the overall color of image content when used as a "global" feature. A color space is defined as a model representing color in terms of intensity values. There are different colors models: RGB, Lab, HSV, HSI, YCbCr, etc. Each of these has got specific applications and also has got advantages and drawbacks. Based on our application we need to convert from one color space to another. All the images are in RGB color model, because of the non-uniformity of RGB color space we need to convert them to the suitable color space. The HSV and L* a* b* models are commonly used in color image retrieval system. The non-uniformity of RGB color model is eliminated by L*a*b, HSV, HSI and YCbCr color models.

1) RGB to L*a*b color model conversion*:*

L*a*b* is an international standard for color measurements, adopted by the Commission International d'Eclairage (CIE) in 1976. This color model creates a consistent color regardless of the device used to generate the image. 'L' is the luminance or lightness component, which ranges from 0 to 100, and parameters a'' (from green to red) and 'b' (from blue to yellow) are the two chromatic components, which range from -120 to 120.

The transformation equations for RGB to Lab color model conversion

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$L = 116\left(g\left(\frac{Y}{Y_n}\right)\right) - 16 \quad , \quad a = 500\left(g\left(\frac{X}{X_n}\right) - g\left(\frac{Y}{Y_n}\right)\right) , \quad b = 200\left(g\left(\frac{Y}{Y_n}\right) - g\left(\frac{Z}{Z_n}\right)\right)$$

$$g(t)=\begin{cases} t^{1/3} & ,t > 0.008856 \\ 7.787 + \frac{16}{116} & ,t \le 0.008856 \end{cases} \qquad \text{…..equation (2.1.1)}$$

2) RGB to HSV color model conversion

The HSV stands for the Hue, Saturation and Value. The value represents intensity of a color, which is decoupled from the color information in the represented image. The hue and saturation components are intimately related to the way human eye perceives. HSV is often called HSB (B for brightness). Hue varies from 0 to 1 when color goes from red to green then to blue and back to red. H is then defined modulo 1 as color is seldom mono chromatic, saturation(S) represents the amount of white color mixed with the monochromatic color. Value (V) does not depend on the color, but represents the brightness. So H and S are chrominance and V is intensity.

The transformation equations for RGB to HSV color model conversion

$$V = \max(R, G, B), \qquad S = \frac{V - \min(R,G,B)}{V}$$

$$H = \frac{G-B}{6S}, \ \ if \ \ V = R; \qquad H = \frac{1}{3} + \frac{B-R}{6S}, \ \ if \ \ V = G; \qquad H = \frac{2}{3} + \frac{R-G}{S}, \ \ if \ \ V = B$$

2.1.3. RGB to HSI color model conversion

The HSI stands for the Hue, Saturation and Intensity. The HSI color space is very important and attractive color model for image processing applications because it represents color 's' similarly how the human eye senses colors. The HSI color model represents every color with three components: hue (H), saturation (S), intensity (I).

Before converting from RGB to HSI color model, we normalize RGB values as follows.

r = R / (R + G+B) , r = G / (R + G+B) , r = B / (R + G+B)

Each normalized H, S and I components are obtained by the following expressions.

$$h = \cos^{-1}\left\{\frac{0.5\cdot\left[(r-g)+(r-b)\right]}{\left[(r-g)^2+(r-b)(g-b)\right]^{1/2}}\right\} \qquad h \in [0, \pi] \text{ for } b \le g$$

$$h = 2\pi - \cos^{-1}\left\{\frac{0.5\cdot\left[(r-g)+(r-b)\right]}{\left[(r-g)^2+(r-b)(g-b)\right]^{1/2}}\right\} \qquad h \in [\pi, 2\pi] \text{ for } b > g$$

S=1-3 min(r, g, b); s € [0,1] , i = (R, G, B) / (3 x 255) ; i € [0,1]

h, s and i values are converted in the ranges of [0,360], [0,100] and [0,255] respectively by

H = h* 180 / π ; S = s * 100 and I = I * 255

2.1.4. RGB to YCbCr color model conversion

Y is the luminance component and C_b and C_r are the blue-difference and red-difference chroma components. The conversion equations from RGB to YCbCr color model is given below.

$$\begin{bmatrix} Y & Cb & Cr \end{bmatrix} = \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.00 \\ 112.00 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 & 128 & 128 \end{bmatrix}$$

B. K-NN Classifier

In pattern recognition, the K-nearest neighbor algorithm (K-NN) is a method for classifying objects based on closest training examples in the feature space. K-NN is a type of instance-based learning where the function is only approximated locally and all computation is deferred until classification. The K-nearest neighbor algorithm is amongst the powerful and simplest of all machine learning algorithms: an object is classified by a majority "votes" of its neighbors, with the object being assigned to the class most common amongst its K nearest neighbors (K is a positive integer, typically small). If K = 1, then the object is simply assigned to the class of its nearest neighbor.

The neighbors are taken from a set of objects for which the correct classification is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples.

In the classification phase, K is a user-defined constant and an unlabelled vector (a query or test point) is classified by assigning the label which is most frequent among the K training samples nearest to that query point. The best choice of K depends upon the data; generally, larger values of K reduce the effect of noise on the classification, but make boundaries between classes less distinct. The K indicates the consideration of top values in the classification vector array. K should be odd in order to avoid ties and it should be kept small, since a large K tends to create misclassifications unless the individual classes are well separated. In our experiment, K= 1,3,5 and 7 were selected. With K=1, minimum distance classifier is used for classification.

C. Canberra Distance

The Canberra distance is used to compute the distance between the features. The distance is calculated and used for classification when K=1. The Canberra distance is given by

$$D(M) = \sum_{i=1}^{N} \frac{\left| f_{1_i} - f_{2_i} \right|}{\left| f_{1_i} \right| + \left| f_{2_i} \right|}$$

where f_1 and f_2 are feature vectors for training and testing.

III. FEATURE EXTRACTION

A. Color Features Extraction

The color conversion is performed before extracting color features. The color images are recognized by quantifying the distribution of color throughout the image and change in the color. The quantification is obtained by computing mean and standard deviation for a given image. The color features represent the global characterization of an image.

The mean and standard deviation are the features extracted as color features. The standard deviation and mean are calculated using the formulae as given below.

Standard Deviation =

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}.$$

$$\text{Mean} = \mu = \frac{1}{N}\sum_{i=0}^{N-1} x_i$$

The total four color features are extracted from each of two color channels from color model. In L*a*b color model, ‘a’ and ‘b’ are the color channels hence two features from each color channel are extracted. Similarly, ‘H’ and ‘S’ in HSV and HSI color models and ‘Cb’ and ‘Cr’ from YCbCr color model respectively.

B. Global Features Extraction

A cumulative histogram is a mapping that counts the cumulative number of observations in all of the bins up to the specified bin as shown in fig 3.2.1.

The cumulative histogram M_i of a histogram m_j is defined as:

$$M_i = \sum_{j=1}^{i} m_j.$$

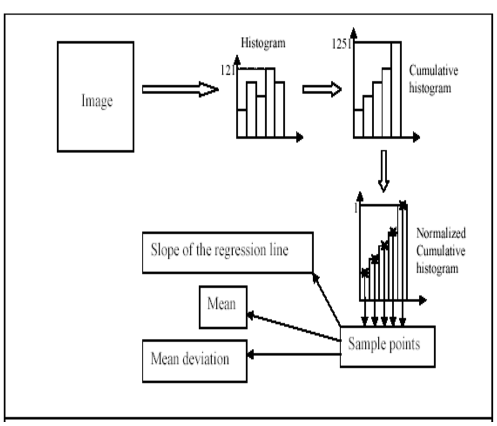

Fig 3.1. Cumulative Histogram

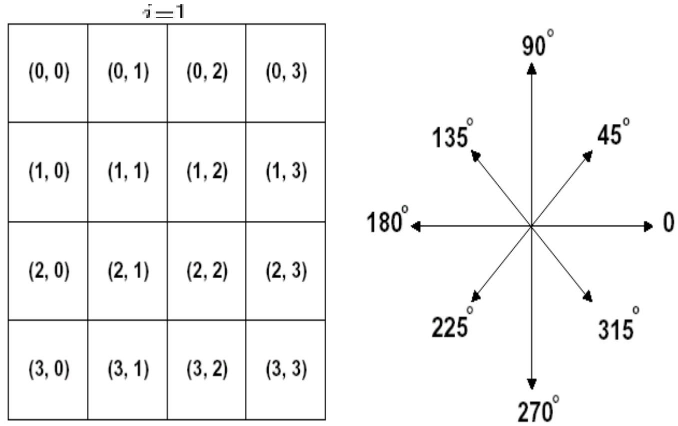

Fig 3.2. Co-occurrence matrix formation

The fig 3.1 shows the formation cumulative histogram from ordinary histogram. The mean, standard deviation and slope of the regression line are the three global features which are extracted from cumulative histogram.

C. Local Features Extraction

The food grains may have similarity in color but exhibit different texture patterns. This motivated us to include texture feature act as local features. We have adopted co-occurrence matrix to obtain texture features. The five local features are extracted from co-occurrence matrix known as Haralick features.

The fig 3.2 shows the formation of co-occurrence matrix. Co-occurrence method is classical in pattern recognition community and has extensively been used on gray scale images [19]. The co-occurrence matrix indicates the position of each pixel with respect to its eight neighbors those are surrounded by each pixel. Let I be a grayscale image coded on m gray levels. Let s ≡ (x, y) be the position of a pixel in I and t ≡ (Δx,Δy) be a translation vector. The co-occurrence matrix Mt is a m x m matrix whose $(i,j)^{th}$ element is the number of pairs of pixels separated by the translation vector t that have the pair of gray levels (i,j). This is a distance of one pixel in eight directions to take into account the eight nearest neighbors of each pixel. The eight matrices obtained were then summed to obtain a rotation invariant matrix M. Let us quote that since Mt(i,j)=M-t(j,i), M is symmetric [11]. Haralick assumed that the texture information is contained in this matrix and texture features are then calculated from it [20]. Haralick extracted 14 parameters from the co-occurrence matrix, but only five are commonly used because it was shown that the five sufficed to give good results in a classification task and are listed in table 3.1.

TABLE 3.1. LIST OF HARALICK FEATURES

Sl.No.	Haralick Features	Equation
1.	Homogeneity	$E = \sum_i \sum_j (M(i,j))^2$
2.	Contrast	$C = \sum_{k=0}^{m-1} k^2 \sum_{\lvert i-j \rvert = k} M(i,j)$
3.	Correlation	$Cor = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)M(i,j)}{\sigma_i \sigma_j}$
4.	Entropy	$H = \sum_i \sum_j M(i,j) \log(M(i,j))$
5.	Local homogeneity	$LH = \sum_i \sum_j \frac{M(i,j)}{1+(i-j)^2}$

IV. EXPRIMENTAL SET UP

A. Food Grains Image Sample Set

Class-1: Jawar Class-2: Wheat Class-3: Corn Class-4: Cow Peas Class-5: Red gram

Class-6: Green gram Class-7: Horse gram Class-8: Bengal gram Class-9: Pearl Millet Class-10: Peas

Fig 4.1. Image sample set and their names

B. Methodology

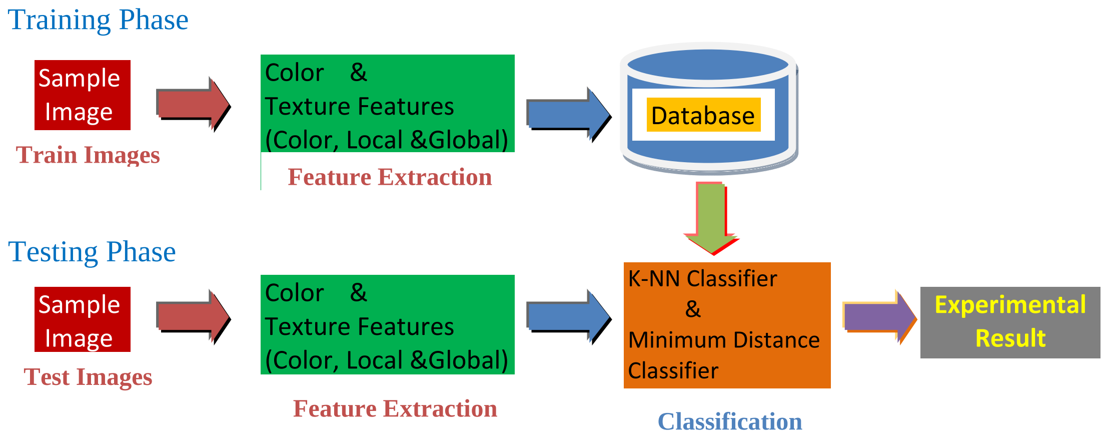

Fig 4.2 Block Diagram of Proposed work

Fig 4.2 shows the block diagram of the proposed work. Images of different food grains are captured under natural light by maintaining fixed background and same distance between camera and food grains for all set of variety of food grains. The acquired images are resized to 1024x1024 and saved as JPEG image. The image is divided into small blocks of size 256x256. The 12 features computed are extracted from all the images and are stored in database. A part of an image is used for training set and remaining part is used for testing set which is tested against training set. Training and testing results are compared and output is given in terms of percentage of classification. The variation in the classification is referred as semantic gap which can be analysed in the form confusion matrix.

C. Algorithm for Computation of Features

The global, local and color features are extracted and the following steps show the flow of computation of features.

Input: Training Image set from database.
Output: Computed features stored in database.
Start:

Step-1: Read image from database and convert RGB color space to suitable color space.
Step-2: Co-occurrence matrix is formed and five Haralick (Local) features are computed.
Step-3: Mean and Standard Deviation are calculated from Chrominance information.
Step-4: Cumulative Histogram is formed to extract global features; viz. mean, standard deviation and slope of regression line.
Step-5: Store all 12 computed features in database.
Step-6: All the above steps are repeated for all the images present in training image set in the database.

Stop

D. Algorithm for Classification

Once the feature computation is performed for all the images, the next procedure is classification. The following steps explain the flow of classification process.

Input: Features stored in database.
Output: Percentage of Classification.
Start:

Step-1: Read test image.
Step-2: Perform necessary color conversion and Compute features.
Step-3: Set the value of K (K=1, 3, 5, 7)
Step-4: Set the path where the computed features are stored in the database.
Step-5: Distance is calculated between training image set and testing image.
Step-6: Sort all the calculated distances in an ascending order.
Step-7: Minimum distance classifier is used for K=1 and K-NN classifier is used for K=3, 5 and 7 to find out each image does belong to particular class.
Step-8: All the above steps are repeated for all test images.
Step-9: The percentage for each class is calculated.
Step-10: Average is calculated.

Stop.

V. EXPRIMENTAL RESULTS AND DISCUSSION

For each texture class, a portion of the image is used for training and the remaining portion is used for testing. Experiments are carried out in L*a*b, HSV, HSI and YCbCr color models. Minimum distance classifier and K-NN classifier are used to analyse the classification performance and the value of K is taken as 1, 3, 5 and 7. The experimental results for different color models and percentage of training sets are shown below in the form of table 5.1 through 5.8.

TABLE-5.1. EXPERIMENTION ON L*a*b COLOR MODEL WITH 25% AND 18.75% TRAINING SET

Training (Tr) image blocks-640 and 480 i.e. 25% and 18.75% Testing image blocks -1920 and 2080 i.e. 75% and 81.25%								
Image Class	**K=1**		**K=3**		**K=5**		**K=7**	
	Tr set-25%	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***
1	94.27	95.19	89.58	93.75	90.62	90.86	90.62	92.7885
2	82.29	77.40	92.70	90.86	96.87	97.59	96.87	96.15
3	98.43	97.11	98.43	97.59	95.83	95.19	95.83	94.71
4	94.79	96.15	93.75	96.15	95.31	94.71	95.31	94.23
5	98.43	98.55	97.91	95.19	95.31	95.30	94.79	95.67
6	86.45	83.65	95.83	83.65	91.66	88.46	91.66	92.30
7	90.62	94.71	92.70	90.86	93.22	93.26	90.62	92.30
8	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
9	100.00	100.00	100.00	96.63	100.00	100.00	100.00	100.00
10	98.43	98.55	98.43	98.55	98.95	99.03	98.95	99.03
Avg	94.37	94.13	95.93	95.04	95.78	95.33	95.46	95.72

Table 5.1 shows the percentage of correct classification in the experimentation on L*a*b color model with 25% and 18.75% training set. It is evident from the table 5.1 that maximum average accuracy of 95.93% in case of 25% training set for K=3 and 95.72% in case of 18.75% training set for K=7 have been achieved.

TABLE-5.2. EXPERIMENTION ON L*a*b COLOR MODEL WITH 12.5% AND 6.25% TRAINING SET

Training (Tr) image blocks-320 and 160 i.e.12.5% and 6.25% Testing image blocks-2240 and 2400 i.e. 87.5% and 93.75%								
Image Class	**K=1**		**K=3**		**K=5**		**K=7**	
	Tr set-12.5%	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***
1	95.08	90.00	88.83	79.16	88.39	77.50	91.51	82.50
2	63.83	52.08	80.80	63.75	92.85	69.16	80.80	74.16
3	97.76	97.91	97.76	98.75	96.87	95.00	95.08	93.33
4	94.19	94.58	92.85	91.66	94.64	91.25	94.64	87.50
5	94.19	92.50	93.30	92.91	92.85	90.41	92.41	90.00
6	76.78	76.66	88.39	90.83	87.50	87.50	91.96	92.50
7	92.85	90.83	91.51	90.00	91.96	91.66	91.07	93.75
8	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
9	99.55	98.75	100.00	100.00	100.00	100.00	100.00	100.00
10	97.76	98.33	97.76	96.66	96.42	96.66	96.42	92.08
Avg	91.20	89.16	93.12	90.37	94.15	89.91	93.39	90.58

Table 5.2 shows the percentage of correct classification in the experimentation on L*a*b color model with 12.5% and 6.25% training set. It is evident from the table 5.2 that maximum average accuracy of 94.15% in case of 12.5% training set for K=5 and 90.58% in case of 6.25% training set for K=7 have been achieved.

TABLE-5.3. EXPERIMENTION ON HSV COLOR MODEL WITH 25% AND 18.75% TRAINING SET

Training (Tr) image blocks-640 and 480 i.e. 25% and 18.75% Testing image blocks -1920 and 2080 i.e. 75% and 81.25%								
Image Class	**K=1**		**K=3**		**K=5**		**K=7**	
	Tr set-25%	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***
1	97.39	93.75	92.70	89.90	93.22	92.78	92.18	91.34
2	53.12	52.88	64.58	63.46	75.52	73.55	69.79	70.67
3	89.58	88.94	85.93	82.69	80.20	76.44	80.72	77.40
4	91.66	93.26	92.70	93.26	89.58	91.34	85.93	87.50
5	93.22	95.67	86.97	89.90	92.18	92.78	91.66	90.86
6	73.95	69.23	81.25	74.03	79.16	70.19	81.25	73.07
7	91.66	88.46	91.66	88.94	93.22	93.26	94.27	91.34
8	97.39	97.59	98.43	98.55	99.47	99.51	99.47	99.51
9	84.37	83.17	83.85	82.69	82.29	81.73	80.72	75.96
10	96.35	96.63	97.91	97.59	95.31	95.67	96.87	96.63
Avg	86.87	85.96	87.60	86.10	88.02	86.73	87.29	85.43

Table 5.3 shows the percentage of correct classification in the experimentation on HSV color model with 25% and 18.75% training set. It is evident from the table 5.3 that maximum average accuracy of 88.02% in case of 25% training set for K=5 and 86.73% in case of 18.75% training set for K=5 have been achieved.

TABLE-5.4. EXPERIMENTION ON HSV COLOR MODEL WITH 12.5% AND 6.25% TRAINING SET

Training (Tr) image blocks-320 and 160 i.e.12.5% and 6.25% Testing image blocks-2240 and 2400 i.e. 87.5% and 93.75%								
Image Class	**K=1**		**K=3**		**K=5**		**K=7**	
	Tr set-12.5%	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***
1	92.85	93.33	87.50	86.25	90.62	93.75	90.17	94.58
2	50.44	31.25	66.07	44.58	79.46	51.25	75.44	64.58
3	87.94	68.33	77.67	52.91	70.53	47.91	70.98	43.33
4	93.30	77.08	92.85	72.50	92.41	74.58	91.07	71.25
5	93.75	88.33	89.73	85.41	88.83	83.75	86.60	76.25
6	57.14	55.00	63.39	65.83	64.28	57.50	71.42	64.16
7	87.05	90.00	87.50	90.41	92.41	93.75	90.17	95.83
8	98.21	99.58	99.55	99.583	99.55	100.00	100.00	100.00
9	79.91	77.50	75.89	79.58	78.12	79.58	72.76	73.33
10	96.87	97.50	95.53	93.33	95.53	89.58	96.42	90.00
Avg	83.75	77.79	83.57	77.04	85.17	77.16	84.50	77.33

Table 5.4 shows the percentage of correct classification in the experimentation on HSV color model with 12.5% and 6.25% training set. It is evident from the table 5.4 that maximum average accuracy of 85.17% in case of 12.5% training set for K=5 and 77.79% in case of 6.25% training set for K=1 have been achieved.

TABLE-5.5. EXPERIMENTION ON HSI COLOR MODEL WITH 25% AND 18.75% TRAINING SET

Training (Tr) image blocks-640 and 480 i.e. 25% and 18.75% Testing image blocks -1920 and 2080 i.e. 75% and 81.25%								
Image Class	**K=1**		**K=3**		**K=5**		**K=7**	
	Tr set-25%	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***
1	96.35	94.23	94.27	90.86	96.35	94.23	94.27	92.78
2	58.33	56.25	65.62	62.98	73.95	72.11	71.35	69.23
3	92.70	87.98	89.58	81.25	85.41	76.92	81.25	74.03
4	97.39	95.19	96.87	94.23	95.83	95.67	93.22	92.30
5	91.66	92.78	88.02	90.86	86.45	83.65	85.41	79.80
6	73.95	73.07	83.33	81.73	77.08	73.07	79.16	72.11
7	93.22	91.82	93.22	91.82	94.79	92.78	94.27	91.34
8	93.75	93.26	95.31	95.19	98.95	99.03	98.95	99.51
9	89.58	88.46	88.02	86.05	85.93	83.17	86.45	80.28
10	97.39	98.076	97.91	98.076	96.87	98.55	96.87	99.03
Avg	88.43	87.11	89.21	87.30	89.16	86.92	88.12	85.04

Table 5.5 shows the percentage of correct classification in the experimentation on HSI color model with 25% and 18.75% training set. It is evident from the table 5.5 that maximum average accuracy of 89.21% in case of 25% training set for K=3 and 87.30% in case of 18.75% training set for K=3 have been achieved.

TABLE-5.6. EXPERIMENTION ON HSI COLOR MODEL WITH 12.5% AND 6.25% TRAINING SET

Training (Tr) image blocks-320 and 160 i.e.12.5% and 6.25% Testing image blocks-2240 and 2400 i.e. 87.5% and 93.75%								
Image Class	K=1		K=3		K=5		K=7	
	Tr set-12.5%	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***
1	89.73	96.25	80.80	91.66	76.78	93.75	74.55	92.50
2	37.50	34.58	63.39	39.16	77.67	47.08	66.51	49.58
3	83.03	63.33	79.46	53.75	76.78	55.00	75.89	54.16
4	98.21	83.33	95.98	70.83	98.21	75.83	94.64	74.58
5	89.73	85.00	85.71	78.33	87.05	68.33	83.48	72.08
6	65.17	61.66	69.64	72.50	62.50	60.00	62.50	58.33
7	89.73	93.33	87.94	88.33	91.51	92.91	90.62	93.75
8	94.64	99.58	99.55	99.58	99.55	99.58	99.55	100.00
9	84.37	82.91	75.89	76.25	79.01	74.58	70.98	64.58
10	97.32	96.66	97.32	96.25	95.53	92.50	95.98	94.16
Avg	82.94	79.66	83.57	76.66	84.46	75.95	81.47	75.37

Table 5.6 shows the percentage of correct classification in the experimentation on HSI color model with 12.5% and 6.25% training set. It is evident from the table 5.6 that maximum average accuracy of 84.46% in case of 12.5% training set for K=5 and 79.66% in case of 6.25% training set for K=1 have been achieved.

TABLE-5.7. EXPERIMENTION ON YCbCr COLOR MODEL WITH 25% AND 18.75% TRAINING SET

Training (Tr) image blocks-640 and 480 i.e. 25% and 18.75% Testing image blocks -1920 and 2080 i.e. 75% and 81.25%								
Image Class	**K=1**		**K=3**		**K=5**		**K=7**	
	Tr set-25%	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***	***Tr set-25%***	***Tr set-18.75%***
1	89.58	90.86	84.89	87.50	90.10	90.86	88.02	88.94
2	71.87	65.86	71.87	71.15	79.16	76.44	73.43	75.00
3	75.52	74.03	71.35	70.19	72.91	70.67	71.35	68.75
4	77.60	82.21	70.31	80.28	82.81	80.76	81.77	81.73
5	98.43	98.07	98.43	97.59	97.39	97.11	98.43	98.07
6	68.75	71.15	78.12	79.80	71.87	72.11	76.04	75.00
7	68.75	66.34	71.35	72.11	71.35	72.11	69.79	70.19
8	98.43	98.55	98.43	98.55	97.39	97.59	97.91	98.07
9	91.66	93.26	89.58	94.23	91.66	93.75	91.14	93.75
10	91.66	82.69	90.62	83.65	92.18	85.09	90.10	84.61
Avg	83.22	82.30	82.50	83.50	84.68	83.65	83.80	83.41

Table 5.7 shows the percentage of correct classification in the experimentation on HSI color model with 25% and 18.75% training set. It is evident from the table 5.7 that maximum average accuracy of 84.68% in case of 25% training set for K=5 and 83.65% in case of 18.75% training set for K=5 have been achieved.

TABLE-5.8. EXPERIMENTION ON YCbCr COLOR MODEL WITH 12.5% AND 6.25% TRAINING SET

Training (Tr) image blocks-320 and 160 i.e.12.5% and 6.25% Testing image blocks-2240 and 2400 i.e. 87.5% and 93.75%								
Image Class	**K=1**		**K=3**		**K=5**		**K=7**	
	Tr set-12.5%	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***	***Tr set-12.5%***	***Tr set-6.25%***
1	92.85	92.91	89.73	90.83	91.51	91.25	90.17	90.83
2	59.37	53.75	65.17	61.25	75.00	69.58	75.44	66.66
3	70.98	72.50	63.39	71.25	68.75	71.66	70.98	66.66
4	86.16	67.08	77.67	53.75	80.35	51.66	78.57	37.91
5	95.53	93.75	96.42	92.50	93.75	92.91	95.08	90.00
6	60.71	61.66	70.53	70.00	58.92	51.66	63.39	66.66
7	54.01	55.83	58.92	54.58	58.92	59.167	57.58	59.58
8	98.66	98.75	98.66	95.83	98.21	95.83	98.66	98.75
9	94.64	90.00	94.64	86.25	97.32	83.75	95.98	84.58
10	79.91	81.66	78.57	80.83	79.91	85.00	79.91	82.91
Avg	79.28	76.79	79.37	75.70	80.26	75.25	80.58	74.45

Table 5.8 shows the percentage of correct classification in the experimentation on YCbCr color model with 12.5% and 6.25% training set. It is evident from the table 5.8 that maximum average accuracy of 80.58% in case of 12.5% training set for K=7 and 76.79% in case of 6.25% training set for K=1 have been achieved.

The average classification results for different percentage of training set and color models are shown in the form of graphs in fig 5.1, 5.2, 5.3 and 5.4

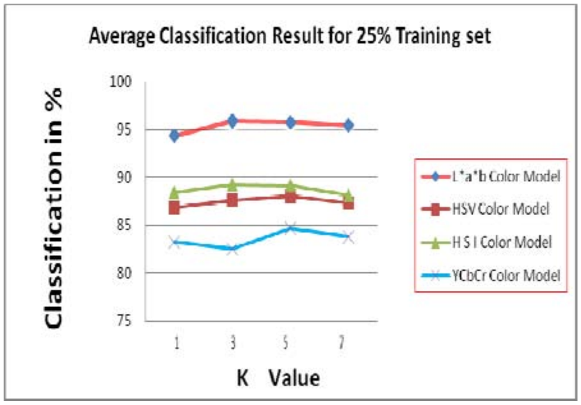

Fig 5.1 Average classification result for 25% training set for different color model

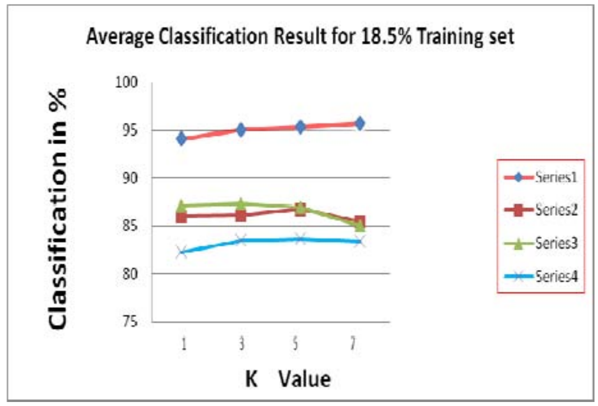

Fig 5.2 Average classification result for 18.5% training set for different color model

Fig 5.1 and fig 5.2 show the average classification results for different color models with 25% and 18.75% training sets. It is evident from the experimental results that maximum classification accuracy has been achieved in case of L*a*b color model.

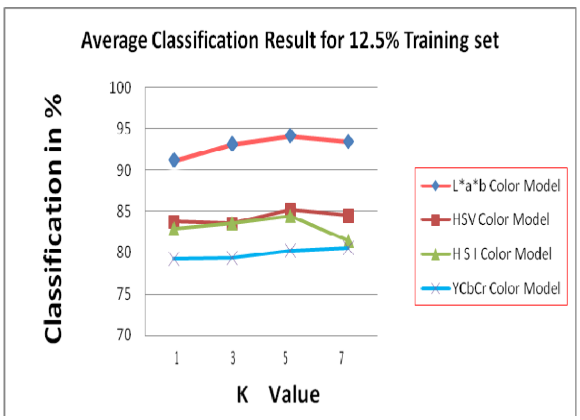

Fig 5.3 Average classification result for 12.5% training set for different color model

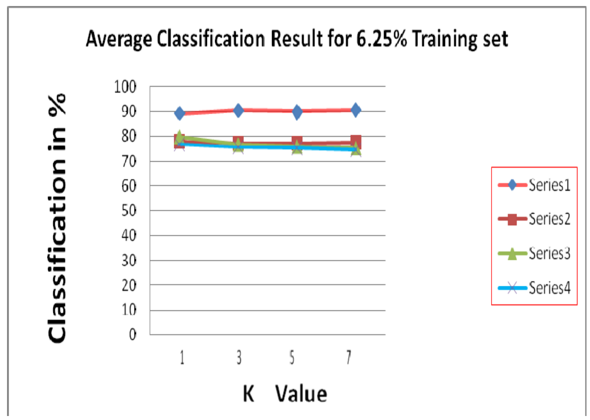

Fig 5.4 Average classification result for 6.5% training set for different color model

Fig 5.3 and fig 5.4 show the average classification results for different color models with 12.5% and 6.25% training sets. It is evident from the experimental results that maximum classification accuracy has been achieved in case of L*a*b color model.

The proposed work is implemented in MATLAB 7. It is observed that when the size of the image increases the result of classification also increases. A confusion matrix contains information about actual and predicted classifications performed by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. This gives clear idea about correct and erroneous classification. From this, one can know where exactly classification goes wrong and to which other class it is misclassifying. This is the gap between human vision and computer vision system-known as semantic gap.

VI. CONCLUSIONS

In this paper, a very simple method is proposed for classification of food grains which does not require performing of pre-processing and thus overcoming the disadvantages like tediousness and time consumption. The proposed method is robust in terms of noise and works with any size of food grain image which is evident from the experimentation. A method for extracting texture features has been presented using co-occurrence matrix (local) features and cumulative histogram (global) features as well as chromatic features. Experiment is carried out using different food grains image sets in L*a*b, HSV, HSI and YCbCr color models with maximum quantization level. The features obtained are used for classification using minimum distance classifier and K-NN classifier.

The classification is performed in two phases: Feature extraction and Classification. Robustness of the system is evident on the feature set used. Also a study on misclassification is carried out in terms of Confusion Matrix. The classification accuracy is analyzed by setting different K values which is presented in the form of table, Block size, training set and testing set. It is evident from the experimentation that the percentage of accuracy is increased by increasing the block size. It is also observed that for K=5 the percentage of correct classification is high and hence K=5 is optimal in most of the cases.

REFERENCES

[1] Lai FS, Zayas I, Pomeranz Y. Application of pattern recognition techniques in the analysis of cereal grains. Cereal Chemistry. 1986;
[2] 63(2):168–174.
[3] Hawk A L; Kaufmann H H; Watson C A Reectance characteristics of various grains. Cereal Science Today, 1970, 15, 381-384
[4] Majumdar S, Jayas DS, Hehn JL, Bulley NR. Classification of various grains using optical properties. Canadian Agric Eng. 1996;
[5] 38(2):139–144.
[6] Neuman, M., H.D. Sapirstein, E. Shwedyk and W. Bushuk. 1989b. Wheat grain color analysis by digital image processing Journal of
[7] Science, Volume 10, Issue 3, November 1989, Pages 175-182
[8] Huang, X.Y., Li, J., Jiang, S., 2004. Study on identification of rice varieties using computer vision
[9] Majumdar, S. and D.S. Jayas. 2000a. Classification of cereal grains using machine vision. I. Morphology models. Transactions of the
[10] ASAE 43(6):1669-1675.
[11] Majumdar, S. and D.S. Jayas. 2000b. Classification of cereal grains using machine vision. II. Color models. Transactions of the ASAE
[12] 43(6):1677-1680.
[13] Majumdar, S. and D.S. Jayas. 2000c. Classification of cereal grains using machine vision. III. Texture models. Transactions of the
[14] ASAE 43(6):1681-1687.
[15] Majumdar, S. and D.S. Jayas. 2000d. Classification of cereal grains using machine vision. IV. Combined morphology, color, and texture
[16] models. Transactions of the ASAE 43(6):1689-1694.
[17] Sanjivani Shantaiya, Mrs.Uzma Ansari. Identification of Food Grains and Its Quality Using Patten Classification. Special Issue of
[18] IJCCT Vol. 2 Issue 2, 3, 4; 2010 for International Conference [ICCT-2010], 3rd-5th December 2010.
[19] Haralick, R.M., Shanmugam. K, and Dinstein. I. 1973. Textural features for image classification. IEEE Trans. on Systems, Man, and
[20] Cybernetics, SMC- 3: 610-621.
[21] Anami B.S., Burkpalli,V., Angadi, S.A. Patil, N.M. (2003), “Neural network approach for grain classification and gradation”,
[22] Proceedings of the second national conference on document analysis and recognition, held at Mandya , India, during 11-12 July, 2003.,
[23] pp. 394-405.
[24] B. S. Anami, D. G. Savakar, Aziz Makandar, and P.H. Unki (2005).” A neural network model for classification of bulk grain samples
[25] based on color and texture”. Proceedings of International Conference on Cognition and Recognition, held at Mandya, India, on 22 &
[26] 23 December 2005 .pp. 359– 368.
[27] B. S. Anami, D. G. Savakar, P. H. Unki and S.S. Sheelawant (2006). “An Artificial Neural Network Model for Separation,
[28] Classification and Gradation of Bulk Grain samples”. IEEE First International Conference on Signal and Image Processing held at
[29] Hubli , India during 7-9 December 2006 .pp 511-520.
[30] Bertalmio,M. Vese,L. Sapiro,G. Osher,S. (2003)” Simultaneous structure and texture image inpainting” IEEE Computer Society
[31] Conference on Computer Vision and Pattern Recognition, Proceedings. Volume: 2 ,pp, 707-712.
[32] BianRu Li; Yue Qi; XuKun Shen,(2005) "An image inpainting method," . Ninth International Conference on Computer Aided Design
[33] and Computer Graphics , pp. 7-10
[34] Haralick, R.M., Shanmugam, K., and Dinstein, I.(1973), “Texture features for image classification”, IEEE Trans. on Syst.,Man, and
[35] cybern, SMC-3:610-621.
[36] Keefe, P.D. (1992), “A dedicated wheat grading system”, Plant Varieties and Seeds, vol. 5, pp. 27-33.
[37] Zhang, J., and Tan. T. 2002. Brief review of invariant texture analysis methods. Pattern Recognition 35:735-747.
[38] Haralick, R.M., 1979. Statistical and structural approaches to texture. Proceeding of the IEEE 67:786-804.
[39] Neelamma K. Patil, Ravi M. Yadahalli (2011), “Clasification of Food Grains Using HSI Color Model by Combining Color and Texture
[40] Information without Performing Preprocessing and Segmentation”, second International Conference on Communication, Computation,
[41] Management & Nanotechnology 2011 (ICN-2011), held at Bhalki, India on September 23-25, 2011.

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