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Comparison of Six Color Models for Variety Identification of Four Paddy Grains

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***Abstract*—** The performances of six color models and their features are compared for classification of Karjat-6, Karjat-2, Ratnagiri-4 and Ratnagiri-24 the four paddy varieties. Total of 15 color features-mean, standard deviation, variance, skewness and kurtosis for each channel are extracted from the high-resolution images of kernels and used as input features for classification. Different feature models consisting of the combination of the above features (MSVSK and MSV) are tested for their ability to classify these cereal grains. Effect of using different features on the accuracy of classification is studied. The most suitable feature from the feature set for accurate classification is identified. The accuracy percentage for YCbCr-MSVSK[1] is 71.2 % and YCbCr –MSV[1] is 65.4%. The MSVSK feature set outperformed the MSV feature set in most of the instances of classification. Similarly YCbCr color model performed well as compared to rest of the color models.

***Keywords*—** Mean, Neural-Network, Standard-deviation, Skewness, Kurtosis and Variance.

I. INTRODUCTION

The objective of this research is to identify and classify grain kernels of four paddy types using different color models and find which color model is most suitable for classifying the seeds along with this the objective is also to find which feature set is suitable for classification.

Grain kernels considered as agricultural objects are of variable sizes, shapes, colors and textures. The accuracy of the classifying algorithm depends on the extracted features which can be further processed to identify the class of the seed. The precision of computer vision can further be exploited to detect the seeds infected by insects or to detect damaged grain kernels. This process of perfectly classified seeds without any damage or infections is essential to increase the productivity of specific grains [1]. The main objective of this study is to extract Fifteen Color features and form two different feature-sets viz. MSVSK and MSV feature set for the six color models, to compare the performance of two feature-sets for the six color models for classification of K6, K2, R4 and R24 paddy types, to find the most suitable Color model from the six color models for accurate classification, to find the most suitable Feature set from the two feature-sets viz. MSVSK and MSV feature set.
The contribution of this paper is Different feature models consisting of the combination of the above features (MSVSK and MSV) are tested for their ability to classify these cereal grains.

Rest of the paper is organized as follows, Section I contains the introduction, Section II contains the related work of color features and neural network, Section III contain the Methodology, Section IV describes results and discussion, Section V concludes research work with future directions.

II. RELATED WORK

i. Color Features

The work in seed color feature extraction has been reported in [2] and Table-I below shows the related work for color feature extraction at a glance.

Table 1
Related work at a glance

Reference	Number of color features	Other Features	Seed used	Methodology	Accuracy
Cao Weishi et al., 2012 [3]	21	---	Maize	DWT and BPNN	94.5%

Chandra B. Singh et al., 2010 [4]	24	Shape and texture	Wheat	NN	Healthy:96.4% Insect damaged: 91-100%
H.K. Mebatsion et al., 2013 [5]	5	Shape	Wheat,oats,rye	NN	99
J. Paliwal et al., 2003a [6]	20	Shape and texture	Wheat,barley,oats	BPNN	90%
J. Paliwal et al., 2003b [7]	20	Shape and texture	Wheat,barley,oats	BPNN) and non-parametric statistical classifier	96%
Kantip et al. 2011 [8]	6	Texture	Corn	SVM	normal seed - 95.6%, defect seed - 80.6%
Li Jingbin et al., 2012 [9]	12	Shape	Cotton	BPNN	90%
Marian Wiwart et al.,2012 [10]	36	Shape	Wheat	PCA	90.27%
Min Zhao et al., 2011 [11]	12	Shape and texture	Three corn varieties	GA and SVM	94.4%
N.S.Visen et al., 2001 [12]	4	Shape	Wheat,oats,rye	probabilistic neural network (PNN), general regression neural network (GRNN), Ward network and back propagation network (BPN).	96.7-98.7%
Pablo et al., 2002; 2005 [13,14]	4	Shape and texture	Weed	naïve bayes classifier, single ANN	60.2-81.6%
Xiao et al., 2010 [15]	28	Shape and texture	five corn varieties	BPNN	88-100% for five different variety of seeds

ii. Neural Network

Some of the recent [7, 12, 16] however, has shown the potential of using artificial neural networks for classification of agricultural products. Artificial neural networks have the potential to solve problems in which some inputs and the corresponding output values are known, but the relationship between the inputs and outputs is not well understood. These conditions are commonly found in grain inspection problems.

Neural networks, which perform faster classification as compared to most of their statistical counterparts, might provide a solution to the problem of slow classification [15]. Statistical pattern classifiers, which are based on Bayes' minimum error rule [17], have so far been the tool of choice for most of the research in this field.

III. METHODOLOGY

The block diagram for the proposed methodology is as shown in Fig. 1. The steps are as follows:

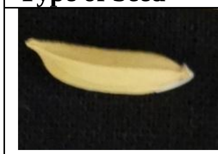
i. Material and Grain samples

Sony Make 18.9 Megapixels Digital camera, Images of four Paddy seeds. The unclean commercial samples used in this study, of four paddy grains- K6, K2, R4 and R24 were collected from the Seed Testing Laboratory-Pune, India.

ii. Image capturing

The images are acquired using above specified digital camera with the kernels placed in such a manner that they don't touch each other. The saved images had the following parameters: 4896 × 3672 resolution, 350 dpi, 24-bit depth, JPG format. The sample images and number of seeds for the specific type is shown in the Table II.

Table-2
Type of different variety of grains and number of seeds

Type of Seed	No. of seeds	Type of Seed	No. of seeds
 K-6	3397	 K-2	1863
 R-4	1780	 R-24	1919

iii. Image pre-processing

The image analysis software is developed in Matlab version 7.12.0.635 (R2011a). Image segmentation and necessary morphological filtering is done as a part of image pre-processing. For all color models, fifteen color features pertaining to mean, standard-deviation, variance, skewness and kurtosis are extracted and then used in different combination for assessing the performance.

a. Feature extraction

A color space is a mathematical representation of a set of colors. The three most popular color models are RGB(used in computer graphics), YUV, YCbCr (used in video systems) and CMYK (used in color printing). Other models such as HSI and HSV were derived because the above color spaces are not directly related to hue, saturation and brightness [18]. CIE is popular for use in measuring reflective and transmissive objects.

Color models

RGB

RGB is an additive color system based on tri-chromatic theory. Often found in systems that use a CRT to display images. RGB is easy to implement but non–linear with visual perception. It is device dependent and specification of colors is semi–intuitive. RGB is very common, being used in virtually every computer system as well as television, video etc. The RGB model forms its gamut from the primary additive colors of red, green and blue. When red, green and blue light is combined it forms white. Computers generally display RGB using 24-bit color. In the 24-bit RGB color model there are 256 variations for each of the additive colors of red, green and blue. In the RGB color model, colors are represented by varying intensities of red, green and blue light. The intensity of each of the red, green and blue components is represented on a scale from 0 to 255 with 0 being the least intensity (no light emitted) to 255 (maximum intensity). For example the Red color would be R=255 G=0 B=0. Black would be R=0 G=0 B=0.

YUV / YCbCr

These are the television transmission color spaces, sometimes known as transmission primaries. YIQ and YUV are analogue spaces for NTSC and PAL systems respectively while YCbCr is a digital standard. These colors spaces separate RGB into luminance and chrominance information. These spaces are device dependent but are intended for use under strictly defined conditions within closed systems.

YUV

The YUV color space

The luminance value Y and the U and V components determine the color itself. YUV color format is based on the characteristics of the human visual perception: Since the human eye is much more sensitive for brightness information compared to color information [18].

Equation to convert between gamma-corrected RGB and YUV are taken from [18]:

$$Y = 0.299R' + 0.587G' + 0.11B'$$
$$U = 0.492(B' - Y)$$
$$V = 0.877(R' - Y) \tag{1}$$

$$R' = Y + 1.140V$$
$$G' = Y - 0.395U - 0.581V$$
$$B' = Y + 2.032U \tag{2}$$

For digital R'G'B' values with a range of 0-255, Y has a range of 0-255, U a range of 0 to ± 112 and V a range of 0 to ±157

YCbCr color space

YCbCr is not absolute color space; it is an offset model of YUV color model [19]. The YCbCr color space is supposed to reduce the redundancy present in RGB color channels and represent the color with satistically independent components [20]. The Luminance information is represented by a single component, Y, and color information is stored as two color-difference components Cb and Cr. Component Cb is the difference between the blue component and a reference value. Component Cr is the difference between the red component and a reference value. Human eyes are sensitive to luminance, but not so sensitive to chrominance, YCbCr color space makes use of this fact to achieve more efficient representation of images. It does so by separating the luminance and chrominance components of a scene, and use less bits for chrominance than luminance. Compared with RGB color space, YCbCr has an explicit separation of luminance and chrominance components.

The transformation from RGB to YCbCr is taken from [21]:

$$\begin{bmatrix} Y \\ C_b \\ Cr \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (3)$$

HSI

The HSI color space is very important and attractive color model for image processing applications because it represents colors similarly how the human eye senses colors, is based on idea of human visual system. The HSI color model represents every color with three components: hue (H), saturation (S), intensity (I). The H referred to hue that measures color purity, S indicates the saturation (the degree of white color embedded in specific color), and I referred to the intensity. This color model also known as HSL, where L indicates the lightness. HSI family of color models use cylindrical coordinates for the representation of RGB points. The importance of HSI color model relies on two main aspects; the I component is separated from the hue H and saturation S which are the chrominance components, and secondly these chrominance components depend on how human perceive this color spectrum [21].

The conversion between each of RGB and HSI are as in defined in [22].

The Hue component describes the color itself in the form of an angle between [0,360] degrees. 0 degree mean red, 120 means green 240 means blue. 60 degrees is yellow, 300 degrees is magenta.

The Saturation component signals how much the color is polluted with white color. The range of the S component is [0,1]. The Intensity range is between [0,1] and 0 means black, 1 means white.

As the above figure shows, hue is more meaningful when saturation approaches 1 and less meaningful when saturation approaches 0 or when intensity approaches 0 or 1. Intensity also limits the saturation values.

Converting from RGB to HSI

$$\begin{cases} H = \theta \quad \text{if } B <= G \\ \quad 360 - \theta \text{ if } B > G \\ \text{with} \end{cases}$$

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

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

$$I = \frac{1}{3}(R+G+B) \quad (4)$$

Converting from HSI to RGB

RG Sector(0°<=H<120°)

$$R = I\left[1 + \frac{S \cdot CosH}{Cos(60^0 - H)}\right]$$

$$G = 3 - (R+B)$$

$$B = I(1-S)$$

GB Sector(120°<=H<240°)

$$H = H - 120^0$$

$$R = I(1-S)$$

$$G = I\left[1 + \frac{S \cdot CosH}{Cos(60^0 - H)}\right]$$

$$B = I - (R+G)$$

BR Sector(240°<=H<360°)

$$H = H - 240^0$$

$$R = I - (G + B)$$
$$G = I(1 - S)$$

$$B = I\left[1 + \frac{S \cdot CosH}{Cos(60^0 - H)}\right] \quad (5)$$

XYZ

One of the first color space defined is CIE XYZ, also referred as X, Y, and Z tristimulus functions, and as CIE color space. Mathematically speaking, the model can be described as luminance component Y along with two chromaticity coordinates X and Z, however, sometimes the XYZ color model is represented by its luminance parameter Y, furthermore, a normalized tristimulus (chromaticity coordinates) can be used as a representative for such model and calculated as in (1) and (2)(denoted by small case xyz) [21]

$$x = \frac{X}{X + Y + Z} \quad \text{and} \quad y = \frac{Y}{X + Y + Z}$$

Since only two coordinates used for color match description, the model represented with on xyplane and the z implicitly evaluated as

$$z = 1 - (x + y) \quad (6)$$

L*a*b

As XYZ, L*a*b is also device independent and considered very important for desktop color. Lab represents every color through three components. The L value represents luminance and ranges from 0 for black to 100 for white in uniform steps. The a values (chroma a*) for positive values indicate red and for negative values indicate green (are represented as +a/-a for red/green) and b values (hue b*) for positive values refer to yellow while negative values refer to blue (are represented as +b/-b for blue/yellow). *L** is luminosity, *a** is red/green axis, *b** is yellow/blue axis.

L*a*b* conversion is taken from [23]

$$L^* = \begin{cases} 116\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16 \quad if \ \frac{Y}{Y_n} > 0.008856 \\ 903.3\left(\frac{Y}{Y_n}\right) \quad if \ \frac{Y}{Y_n} \le 0.008856 \end{cases}$$

$$a^* = 500 * \left(f(X/X_n) - f(Y/Y_n)\right)$$
$$b^* = 200 * \left(f(Y/Y_n) - f(Z/Z_n)\right) \quad (7)$$

Where

$$f(t) = \begin{cases} t^{1/2} & if \quad t > 0.008856 \\ 7.787 * t + 16/116 & if \quad t \le 0.008856 \end{cases}$$

*L** scales from 0 to 100.

iv. Color Feature Extraction

The feature extraction algorithm extracted fifteen color features of individual kernels for each grain type for each color model. Color features of kernels included mean, standard deviation, variance, skewness and kurtosis of the RGB, YUV, YCbCr, HSI,XYZ, LAB color models. Every color is defined by 3 or more values or 3 channels. Color features are calculated for all the three channels in all the six color models.

1. Mean : μ

Mean is the average color value in the image.

$$\mu = \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} / mn \quad (8)$$

Image is of size m x n, x_{ij} : pixel value of i_{th} row and j_{th} column

2. Standard deviation : σ

Deviation means how far from normal. Standard deviation is a measure of how spread-out numbers are.

$$\sigma = \sqrt{\text{var}iance} \quad (9)$$

3. Variance is average of squared difference from mean. It is calculated as follows:

$$\text{var}iance = 1/nm \sum_{i=1}^{n} \sum_{j=1}^{m} (x_{ij} - \mu)^2 \quad (10)$$

4. Skewness: Skewness is a measure of degree of asymmetry in the distribution. Values are positive, zero and negative. Positive values indicate left of mean, Negative values indicate right of mean, zero indicate evenly distributed.

$$skewness = \sqrt[3]{1/nm \sum_{i=1}^{n} \sum_{j=1}^{m} (x_{ij} - \mu)^3} \quad (11)$$

5. Kurtosis: Kurtosis is the fourth color moment and provides information about shape of color distribution. It is a measure of how flat or tall the distribution is in comparison to normal distribution. High value is good it shows low noise and resolution.

To study the effect of various features on the classification ability of the ANN, First fifteen features concerning mean, standard-deviation, variance, skewness and kurtosis of six color models are used for classifying the grains in four categories. Then, nine features concerning mean, standard-deviation and variance are used for classifying the grains. These feature sets are referred as MSVSK and MSV respectively.

v. Artificial neural network architectures

ANN classifier is emerging as the best suited classifiers for pattern recognition which are regarded as an extension of many classification techniques. They are based on the concept of biological nervous system. NNs explore many hypotheses simultaneously using massive parallelism instead of sequentially performing a programme of instructions.

Pattern classification was done using a Two-layer (i.e. one-hidden-layer) backpropagation supervised neural networks with a single hidden layer of 20 neurons with LM training functions. The choice of the BPN classifier was based on previous research conducted by [4].

BPN consists of an input layer, one or more hidden layers, and an output layer and has ability to generalize. The number of nodes was varied to see any significant improvement in performance. As no improvement was observed, the number of nodes as 20 was used to train the network. The trained neural network was tested with the testing samples to find how well the network will do when applied to data from the real world. One measure to find how well the neural network has fit the data, the confusion matrix was plotted across all samples. The fifteen features and later on nine features of six color models are used as inputs to a neural network and the type of the seed as target. Given an input, which constitutes the features of a seed, the neural network is expected to identify the type of the seed which is achieved by neural network training.

IV. RESULTS

The effect of different feature sets (MSVSK and MSV), of six color models on the classification was studied using the selected ANN configuration described above. Table III gives the Sensitivity and Total accuracy for both the feature set of six color models and four variety of grains. The sensitivity and accuracy is calculated as in [1]. Figure 2 shows the plot of accuracy of all color models.

Table.3. Sensitivity for class and Total accuracy%

Seeds	MSVSK		MSV	
	Sensitivity	Total accuracy%	Sensitivity	Total accuracy%
RGB				
K6	12.2	67.0	20.8	64.1
K2	98.8		78.6	
R4	60.7		78.4	
R24	99.7		93.4	
YUV				
K6	12.3	67.5	10.7	61.4
K2	98.5		91.5	
R4	64.1		49.3	
R24	99.7		99.5	
YCbCr				
K6	23.9	71.2	11.00	65.4
K2	98.9		97.7	
R4	65.2		56.9	
R24	100		99.7	
HSI				
K6	42.7	33.4	54.9	51.0
K2	13.3		37.4	
R4	26.4		44.6	
R24	91.9		98.9	
XYZ				
K6	20.9	69.9	10.2	60.6

K2	99.5		92.8	
R4	61.7		44.9	
R24	99.7		96.5	
LAB				
K6	16.2	69.1	16.4	62.3
K2	99		97.5	
R4	65.6		32.0	
R24	99.8		99.7	

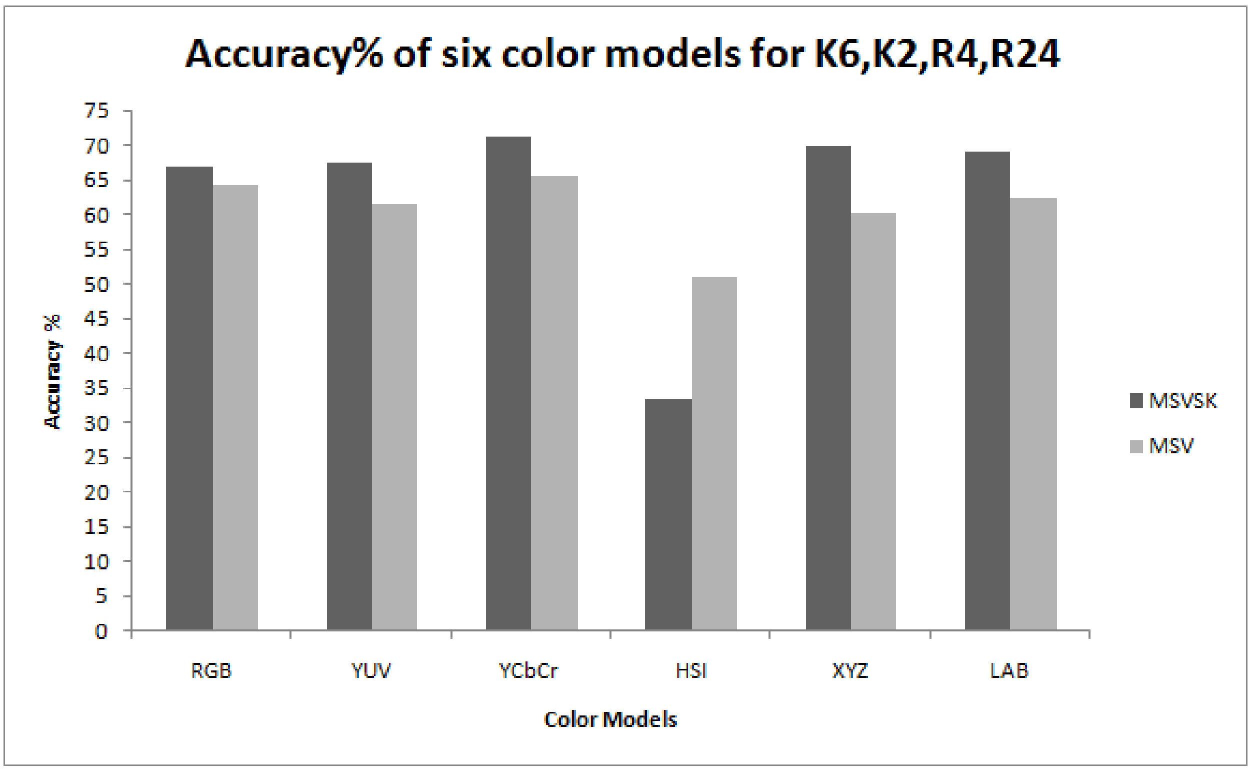


Fig. 2. Plot of Accuracy Vs. Color models

V. CONCLUSION AND FUTURE SCOPE

The classification of grains is done using mean, standard deviation, variance, skewness and kurtosis features of six color models. The assessment of these features is done to find out the best feature set from the two sets (MSVSK and MSV) and the best color model. The results showed that the accuracy of classification of the ANN was best most of the time when MSVSK feature set was used as compared to MSV. Also the accuracy was maximum for YCbCr color model as compared to the other color models used in this study. The acceptable results are given by YCbCr-MSVSK feature set. HSI-MSVSK feature set gave lower accuracy than all other sets. It can be concluded that YCbCr-MSVSK has most important role in identifying the paddy varieties. Human eyes are sensitive to luminance, but not so sensitive to chrominance, YCbCr color space makes use of this fact to achieve more efficient representation of images. This is done by separating the luminance and chrominance components of the image. The accuracy can be improved if also shape and texture features be included in the color feature set.

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Abbrevations used

[1] Mean, Standard-deviation, Variance, Skewness, Kurtosis (MSVSK),
Mean, Standard-deviation, Variance (MSV),
Karjat-6 (K6), Karjat-2 (K2), Ratnagiri-4 (R4), Ratnagiri-24(R24),
Back Propagation Network (BPN), Artificial Neural Network (ANN)

