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Classification of Arecanut based on Color Features

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Abtract: In this paper, classification of arecanut with husk has been proposed using color features of the components of RGB, HSV and YCbCr color spaces of arecanut. Classification is done using kNN and SVM classifiers.

Key Words: Arecanut, Color Features, Classification, kNN, SVM

1. INTRODUCTION

The arecanut palm bearing the scientific name Areca Catechu Linn and included in the tribe Arecae of the family palmae. The palm owes its rating of importance to the fruits known as the arecanut, which forms the principal chewing material in India and in the far eastern countries. Arecanut is almost symbolic of the great culture of some of the oriented nations especially Indians and Indonesians. Betel-nut chewing is as familiar as chewing gum to the Americans (V. Raghavan et al., 1958). It is used in Indian and other South countries as a masticator. It forms one of the ingredients of betel quid commonly in India. It has an integral part in several religious and social ceremonies. Arecanut is largely cultivated in the plains and foot hills of Western Ghats and Eastern regions of India. Production area in different states indicates that Kerala and Assam account for over 90%. Arecanut is grown in Bangladesh, China, Malaysia, Indonesia, Vietnam and Thailand. India accounts for about 57% of world production.

Color and texture of arecanut are the most important parameters that allows for the evaluation of their degree of quality, and existence of faults and also color along with its level of homogeneity influences the degree of acceptance of consumers, as well as the pricing. Today, the increasing technological development and sophistication of modern societies impose new quality standards for the crop producers. Consumers demand more and more information about the products they buy, demonstrating clear preferences for well-informed high-quality products. Human has a prominent role in classification of arecanut. There are several computer based technologies for other crops but there is no computer vision based advanced technology in identifying grades of an arecanut. This leads to time consuming, expensive for labour and inconsistency in classification. Computer vision based technology is required to address the above problem. Color features are the dominant features for classification of arecanut with husk. Texture features are dominant features in classification of arecanut without husk. In this work, arecanut with husk has been considered.

2. RELATED WORK

An image histogram refers to the probability mass function of pixel intensities and a color histogram of an image is nothing but the frequency distribution of color values present in the image. Usually a color quantization phase is performed on the original image in order to reduce the number of colors. A color histogram is frequently used to compare two images because computation of histogram is simple and tend to be robust for small changes in camera viewpoint. Computation of color histogram descriptors depends

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on selection of type of color space, color quantization and number of bins to compute the histogram. Selecting appropriate specifications for computation of a color histogram is a crucial and cumbersome task. However, in MPEG-7 it has been recommended to adopt color models such as hue-saturation-value (HSV), YCbCr, red-green-blue (RGB), and hue-min-max-difference (HMMD) for extraction of color descriptors.

Sezai Sablak et al. (1999) proposed the use of a vector of color histogram peaks as an efficient and effective way for many image indexing problems. K. Konstantinidis et al. (2005) proposed a new fuzzy linking method of color histogram creation based on the L*a*b* color space and provides a histogram which contains only 10 bins. The histogram creation method was assessed based on the performances achieved in retrieving similar images from a widely diverse image collection. The experimental results prove that the proposed method is less sensitive to various changes in images such as lighting variations, occlusions and noise than other methods of histogram creation. Guang-Hai Liu et al. (2013) presented a novel color difference histograms image feature representation method for image retrieval. The unique characteristic in this method is count the perceptually uniform color difference between two points under different backgrounds of colors and edge orientations in L*a*b color space. Chia-Feng Juang et al. (2009) proposed a method that uses color histograms of an object on the hue and saturation (HS) color components of HSI color model as features. George Paschos et al. (2003) proposed a color texture classification method using ratio features extracted from a color histogram. A pairs of bins are combined and computing corresponding count ratios, ratio features are created that characterize the given color texture in an auto-correlative sense.

3. PROPOSED METHODOLOGY

3.1. Segmentation

The first step in arecanut classification is segmentation of arecanut from background. The process of segmentation subdivides an image into its constituent parts or objects. The level to which this subdivision is carried out depends on the problem being solved. That is segmentation should stop when the objects of interest in an application have been isolated. In general, autonomous segmentation is one of the most difficult tasks in image processing. Various image segmentation algorithms have been proposed to achieve efficient and accurate results. Autonomous threshold based segmentation has given good segmentation results for arecanut without changing any parameter value. The major idea used in segmentation in this work is, saturation channel is extracted from HSI color model for segmentation of arecanut from background. Threshold based segmentation is used based on Global image threshold using Otsu method for segmentation of arecanut from background (Rafael C. Gonzalez et al., 2008, 2009).

3.2. Features Extraction

In this method, classification has been done using mean value of color components of RGB, YCbCr and HSV color space of arecanut image. Classification of arecanut with husk has been done to BN and UBN using SVM and kNN classifiers.

Mean color features of color components of RGB, YCbCr and HSV color space have been determined using equations from (1)-(9).

Mean of red component of RGB image
$$\mu_R = \frac{1}{M \quad X \quad N} \sum_{x=1}^{M} \sum_{y=1}^{N} R(x, y) \tag{1}$$

Mean of green component of RGB image
$$\mu_G = \frac{1}{M \quad X \quad N} \sum_{x=1}^{M} \sum_{y=1}^{N} G(x, y) \tag{2}$$

Mean of blue component of RGB image $$\mu_B = \frac{1}{M \quad X \quad N}\sum_{x=1}^{M}\sum_{y=1}^{N} B(x,y) \qquad (3)$$

Mean of yellow component of YCbCr image $$\mu_Y = \frac{1}{M \quad X \quad N}\sum_{x=1}^{M}\sum_{y=1}^{N} Y(x,y) \qquad (4)$$

Mean of chromatic blue component of YCbCr image $$\mu_{Cb} = \frac{1}{M \quad X \quad N}\sum_{x=1}^{M}\sum_{y=1}^{N} Cb(x,y) \qquad (5)$$

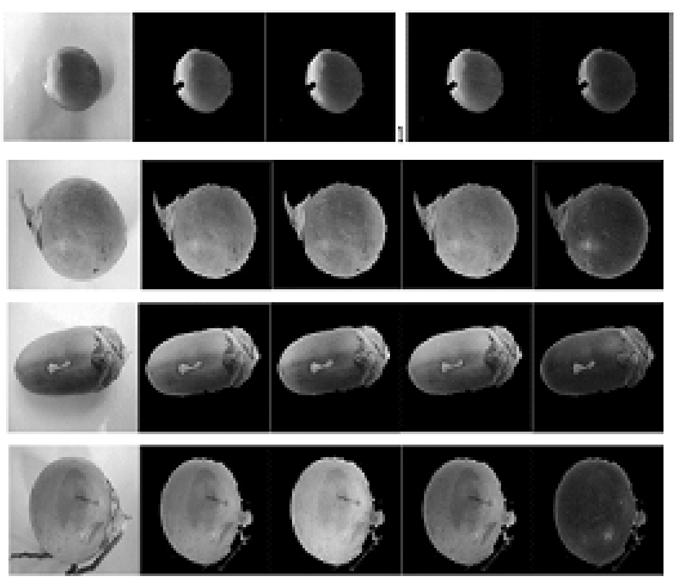
Mean of chromatic red component of YCbCr image $$\mu_{Cr} = \frac{1}{M \quad X \quad N}\sum_{x=1}^{M}\sum_{y=1}^{N} Cr(x,y) \qquad (6)$$

Mean of Hue component of HSV image $$\mu_H = \frac{1}{M \quad X \quad N}\sum_{x=1}^{M}\sum_{y=1}^{N} H(x,y) \qquad (7)$$

Mean of Saturation component of HSV image $$\mu_S = \frac{1}{M \quad X \quad N}\sum_{x=1}^{M}\sum_{y=1}^{N} S(x,y) \qquad (8)$$

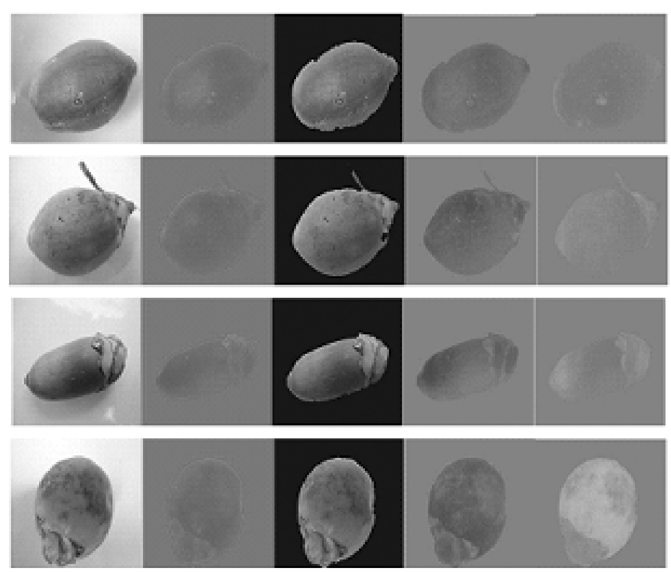
Mean of Value component of HSV image $$\mu_V = \frac{1}{M \quad X \quad N}\sum_{x=1}^{M}\sum_{y=1}^{N} V(x,y) \qquad (9)$$

The segmentation results for RGB, YCbCr and HSV color spaces are shown in Figures 1, 2 and 3 respectively.



(a) (b) (c) (d) (e)

Figure 1: Segmentation Results for RGB Color Space (a) RGB Image. (b) Segmented Image. (c) Red Component of (b). (d) Green Component of (b) and (e) Blue Component of (b).



(a) (b) (c) (d) (e)

Figure 2: Segmentation Results of YCbCr Color Space (a) RGB Image (b) Segmented YCbCr Image (c) Yellow Component of (b). (d) Chromatic Blue Component of (b) and (e) Chromatic Red Component of (b).

3.3. Classification using SVM and kNN

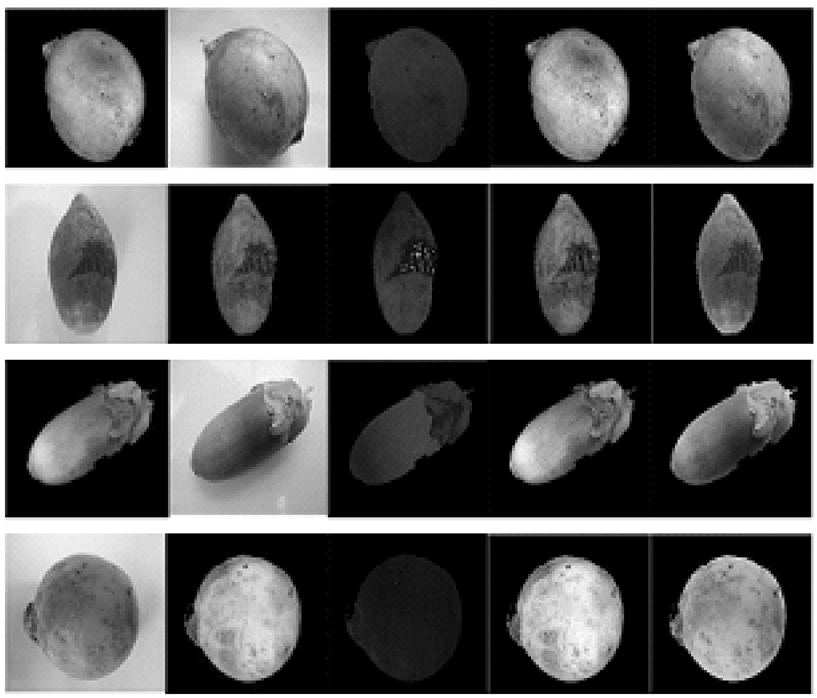
SVM and kNN classifier have been employed for classification of arecanut.

3.4. Support Vector Machines (SVM) Classifier

Given l training arecanut samples $\{x_i, y_i\}$, where $i = 1\ldots l$ where each arecanut has 2 inputs (x_iõR^2), and a class label with one of two classes y_iõ$\{1,-1\}$. Now, all hyperplanes in R^2 are parameterized by a vector (w), and a constant (b), expressed in equation.

$$w.x + b = 0 \tag{10}$$

w is in fact the vector orthogonal to the hyperplane. Given such an hyperplane (w, b) that separates the arecanut data, this gives the function



(a) (b) (c) (d) (e)

Figure 3: Segmentation Results for HSV Color Space (a) RGB Image (b) Segmented HSV Image (c) Hue Component of (b). (d) Saturation Component of (b).and (e) Value Component of (b).

$$f(x) = sign(w.x + b) \tag{11}$$

This correctly classifies the training data. However, a given hyperplane represented by (w, b) is equally expressed by all pairs $\{\lambda w, \lambda b\}$ for λ õ R^+. So we define the canonical hyperplane to be that which separates the data from the hyperplane by a distance of at least 1. That is, considered those satisfy equations (12) and (13).

$$x_i.w + b \geq +1 \quad when \quad y_i = +1 \tag{12}$$

$$x_i.w + b \leq -1 \quad when \quad y_i = -1 \tag{13}$$

or more compactly:

$$(x_i.w + b) \geq 1 \qquad for \quad all \quad i \tag{14}$$

All such hyperplanes have a functional distance ≥ 1. For a given hyperplane (w, b), all pairs {λw, λb} define the exact same hyperplane, but each has a different functional distance to a given data point to obtain the geometric distance from the hyperplane to a data point. Then normalize by the magnitude of w, such that this distance is simply:

$$d((w,b),x_i) = \frac{y_i(x_i.w+b)}{||w||} \geq \frac{1}{||w|} \tag{15}$$

A hyperplane that maximizes the geometric distance is to the closest data points. From equation this is accomplished by minimizing $||w||$ (subjected to the distance constraints). The main method of doing this is with Lagrange multipliers (Christopher J.C. Burges, 1998; Vladimir Vapnik, 1995). The problem details are eventually transformed into:

$$Minimize(\alpha) = \sum_{i=1}^{l} \alpha_i + \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j (x_i, x_j)$$

$$Subjected \quad to: \ \alpha^T y = 0$$

$$0 \leq \alpha \leq C1 \tag{16}$$

where α is the vector of l of non-negative Lagrange multipliers to be determined, and C is a constant. We can define the matrix ($H_{ij} = y_i y_j (x_{i,} x_j)$) and introduce more compact notation:

$$Minimize: \ w(\alpha) = -\alpha^T + \frac{1}{2}\alpha^T H \alpha \tag{17}$$

$$Subjected \quad to: \ \alpha^T y = 0 \tag{18}$$

$$0 \leq \alpha \leq C1 \tag{19}$$

This minimization problem is what is known as a Quadratic Programming Problem (QP). In addition, from the derivation of these equations, it was seen that the optimal hyperplane can be written as:

$$w = \sum_i \alpha_i y_i x_i \tag{20}$$

That is, the vector w is just a linear combination of the training examples. Interestingly, it can also be shown that.

$$\alpha_i(y_i(w.x_i + b) - 1) = 0 \qquad (\forall i) \tag{21}$$

When the functional distance of an example is strictly greater than 1 (when $y_i(w.\ x_i) + b) > 1$), then $\alpha = 0$. So only the closest data points contribute to w. these training examples or which $\alpha_i > 0$ are termed support vectors. They are the only ones needed in defining the optimal hyperplane.

Assuming that, the optimal α must still determine b to fully specify the hyperplane. To do this, take any positive and negative support vector, x^+ and x^-, for which given equations (22) and (23).

$$(w.x^+ + b) = +1 \tag{22}$$

$$(w.x^- + b) = -1 \tag{23}$$

Solving these equations gives us

$$b = -\frac{1}{2}(w.x^{+} + w.x^{-}) \tag{24}$$

Now, there is a need for the constraint using equation (19)

$$\alpha_i \leq C \quad for \quad all \quad i$$

When $C = \infty$, the optimal hyperplane will be the one that completely separates the data. For finite *C*, this changes the problem to finding a soft-margin classifier, which allows for some of the data to be misclassified. The constant *C* is a tunable parameter, higher *C* corresponds to more importance on classification of all the training data correctly, lower *C* results in a more flexible hyperplane that tries to minimize the margin error for each example. Finite values of *C* are useful in situations where the data is not easily separable.

3.5. Nearest Neighbor (kNN) Classifier

In supervised learning, training samples and test samples of arecanut are considered. A training sample is an ordered pair h_x, y_i where *x* is color features and *y* is a label. A test sample of an arecanut is an instance *x* with unknown label. The goal is to predict labels for test samples. The kNN classifier has two stages. The first is the determination of the nearest neighbors and the second is the determination of the class using those neighbors. Let us assume that there is a training arecanut dataset *D* made up of (x_i) õ [1, |*D*|] training samples. The examples are described by a set of features *F*. Each training arecanut sample is labeled with a class label y_j õ *Y*. Objective is to classify an unknown arecanut *q*. For each x_i õ *D* can be calculated the distance between *q* and x_i as follows:

$$d(q, x_i) = \sum_{f \varepsilon F} \delta(q_f, x_{if}) \tag{25}$$

There are a large range of possibilities for the distance metric. A basic version for continuous and discrete attributes would be:

$$\delta(q_f, x_{if}) = \begin{array}{lll} 0 & f & discrete \quad and \quad q_f = x_{if} \\ 1 & & discrete \quad and \quad q_f \neq x_{if} \\ q_f - x_{if} & f & continuous \end{array} \tag{26}$$

The *k* nearest neighbors is selected based on this distance metric. Then there are a variety of ways in which the *k* nearest neighbors can be used to determine the class of *q*. The most straightforward approach is to assign the majority class among the nearest neighbors to the query. It will often make sense to assign more weight to the nearer neighbors in deciding the class of the query. A fairly general technique to achieve this is distance weighted voting where the neighbors get to vote on the class of the query case with votes weighted by the inverse of their distance to the query.

$$Vote(y_j) = \sum_{c=1}^{k} \frac{1}{d(q, x_c)^n}(y_j, y_c) \tag{27}$$

Thus the vote assigned to class y_j by neighbor x_c is 1 divided by the distance to that neighbor, i.e. $1(y_j, y_c)$ returns 1 if the class labels match and 0 otherwise. The value *n* would normally be 1 but values greater than 1 can be used to further reduce the influence of more distant neighbors.

4. RESULTS AND DISCUSSION

The most common commercial variety of arecanut are considered for this study. The database contains 400 images from 15 different agricultural fields. Images were resized to 300 × 300 pixel resolution for reasonable computation speed. The k-fold cross validation-method (Pang-Ning Tan et al., 2009) has been used for evaluating the performance of the kNN and SVM classifier. The parameter *k* is 10 in our case i.e., 10 folds of data.

Table 1. The experimental results have been generated for the color components of RGB, YCbCr and HSV color spaces using kNN Classifier.

Table 1
The Experimental Results Have Been Generated For The Color Components Of Rgb, Ycbcr And Hsv Color Spaces Using Svm Classifier

Color Space	*Color Components*	*Success Rate*
	Green and Blue	48.95
RGB	Red and Blue	97.91
	Red and Green	100
	Yellow and Chromatic Blue	75
YCbCr	Yellow and Chromatic Red	98.95
	Chromatic Blue and Chromatic Red	100
	Saturation and Value	91.66
HSV	Hue and Value	100
	Hue and Saturation	100

Table 2
The Experimental Results Have Been Generated For The Color Components Of Rgb, Ycbcr And Hsv Color Spaces Using Svm Classifier.

Color Space	*Color Components*	*Success Rate*
	Green and Blue	41.66
RGB	Red and Blue	92.64
	Red and Green	99.50
	Yellow and Chromatic Blue	71.56
YCbCr	Yellow and Chromatic Red	99.01
	Chromatic Blue and Chromatic Red	99.01
	Saturation and Value	83.82
HSV	Hue and Value	99.50
	Hue and Saturation	99.50

Results obtained for color components of RGB, YCbCr and HSV color spaces are shown in Table 1 and 2 for kNN and SVM Classifiers respectively. The Red and Green color components of RGB, Chromatic Blue and Chromatic Red of YCbCr, Hue and Saturation, and Hue and Value of HSV color spaces have given success rate of 100%. The results obtained for color components of RGB, YCbCr and HSV color spaces using kNN and SVM classifiers shown in Tables 1 and 1 are plotted in Figures 4-6.

Figure 4(a) reveals that more number of interclass overlapping is occurred for the data points of green and blue components of RGB arecanut image. Figure 4(b) reveals that overlapping with minimal points is occurred for the data points of red and blue components of RGB arecanut image. Figure 4(c) reveals that interclass overlapping is not occurred for the data points of red and green components of RGB arecanut

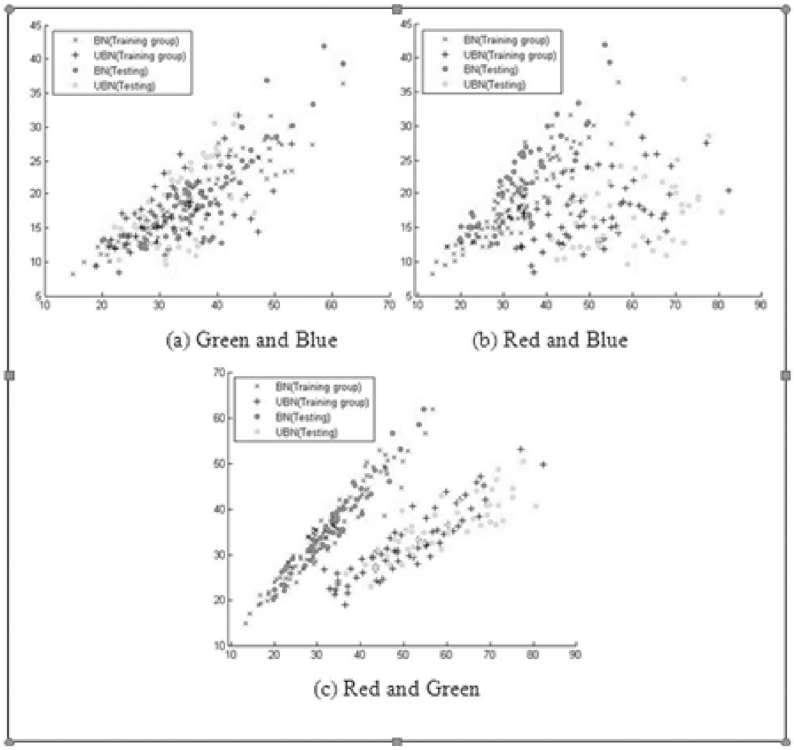


Figure 4: Plot of Mean value of color components of RGB Color Space using kNN classifier.

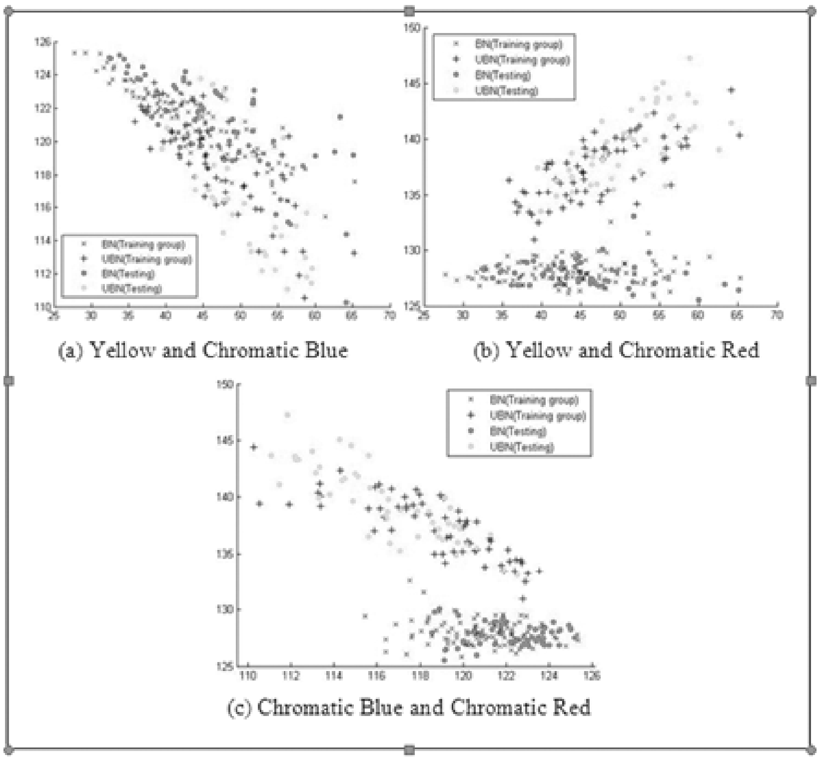


Figure 5: Plot of Mean value of color components of YCbCr Color Space using kNN classifier

image, this shows that red and green components features have highest discrimination power and have given excellent results.

Figure 5(a) shows that interclass overlapping is occurred for the data points of yellow and chromatic blue components of YCbCr arecanut image. Figure 5(b) shows that overlapping is occurred for the data points of yellow and chromatic red at minimal number of points. Figure 5(c) reveals that interclass overlapping is not occurred for the data points of chromatic blue and chromatic red, this shows that red and green components features have highest discrimination power and have given excellent results.

Figure 6(a) shows that interclass overlapping is occurred for the data points of Saturation and Value components of HSV color space of arecanut. Whereas Figures 6(b) and 6(c) shows that data points of Hue verses Value and Hue verses Saturation have minimal interclass overlapping points occurred. It is concluded that Hue verses Value and Hue verses Saturation have higher discrimination power and these features have given good results.

Figure 7(a) shows that more number of interclass overlapping is occurred for the data points of green and blue components of RGB arecanut image. Figure 7(b) reveals that interclass overlapping is occurred at minimal points for the data points of red and blue components of RGB arecanut image. Figure 7(c) reveals that interclass overlapping is occurred with minimal points for the data points of red and green components of RGB arecanut image, this shows that red and green components features have higher discrimination power and have given excellent results when SVM classifier is used.

Figure 8(a) shows that interclass overlapping is occurred for the data points of yellow and chromatic blue components of YCbCr arecanut image. Figures 8(b) and 8(c) shows that interclass overlapping is

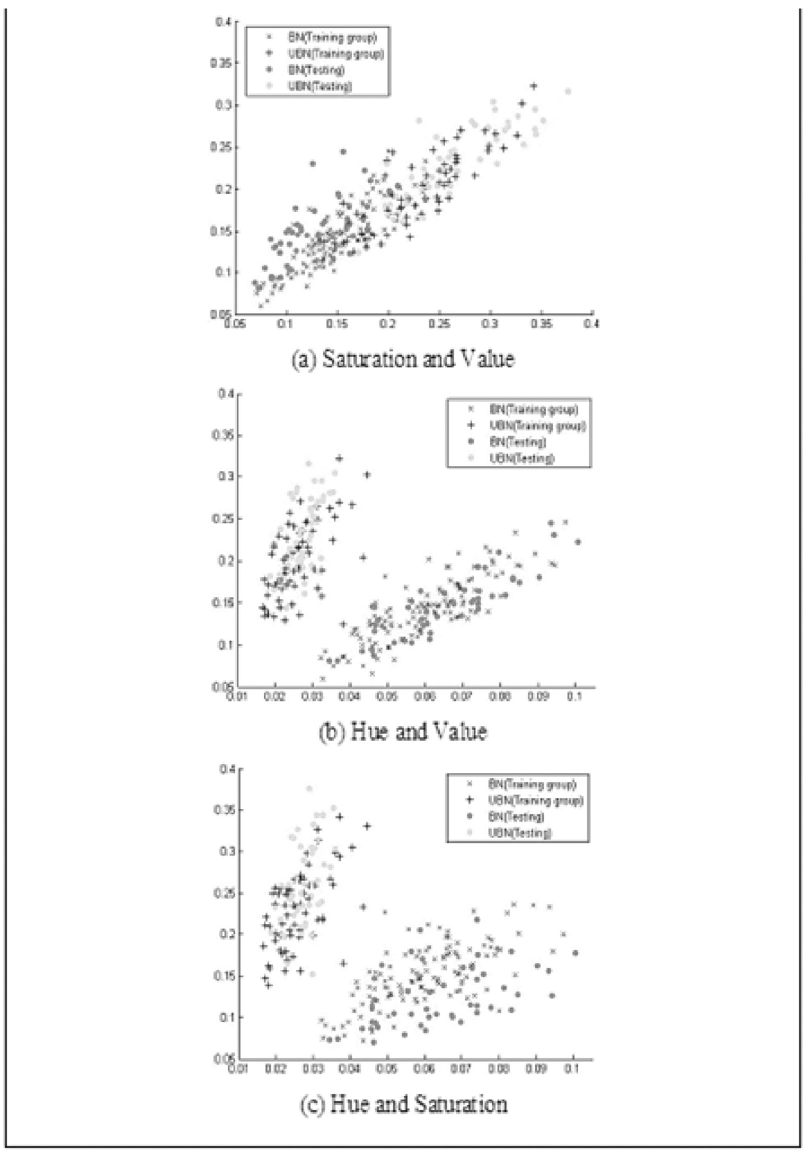


Figure 6: Plot of Mean value of color components of HSV Color Space using kNN classifier.

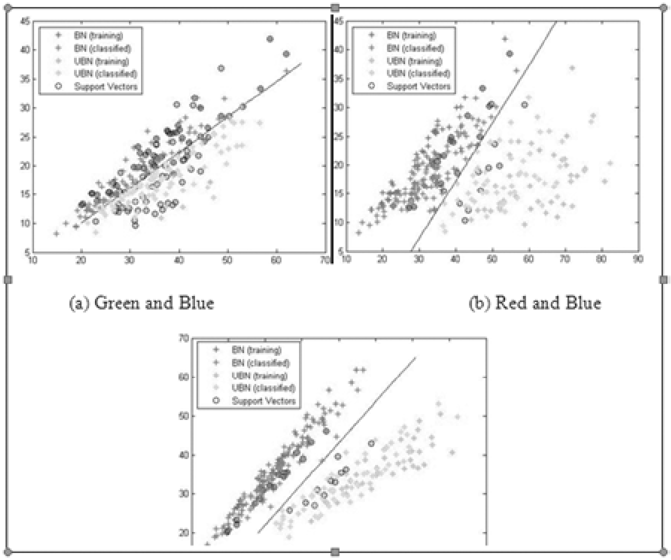


Figure 7: Plot of Mean value of color components of RGB Color Space using SVM classifier.

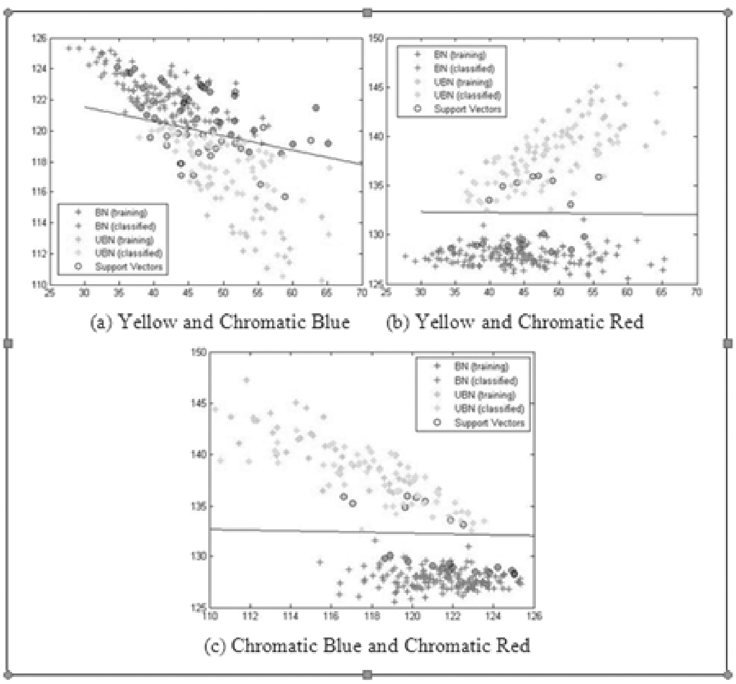


Figure 8: Plot of Mean value of color components of YCbCr Color Space using SVM classifier.

occurred for the data points of yellow verses chromatic red and chromatic blue verses chromatic red, this shows that yellow verses chromatic red and chromatic blue verses chromatic red features have highest discrimination power and have given excellent results.

Figure 9(a) shows that moderate number of interclass overlapping points occurred for the Saturation and Value components of HSV color space of arecanut. The figures 9(b) and 9(c) show that interclass overlapping is occurred at minimal points for the data points of Hue verses Value and Hue verses Saturation. It is concluded that Hue verses Value and Hue verses Saturation have higher discrimination power of classification and these features have given excellent results when SVM classifier is used for classification.

V. CONCLUSION

Sigma control limits. Color features of the components of RGB, YCbCr and HSV have been used for classification. Results have been evaluated using SVM and kNN Classifiers. The Red verses Green color components of RGB,

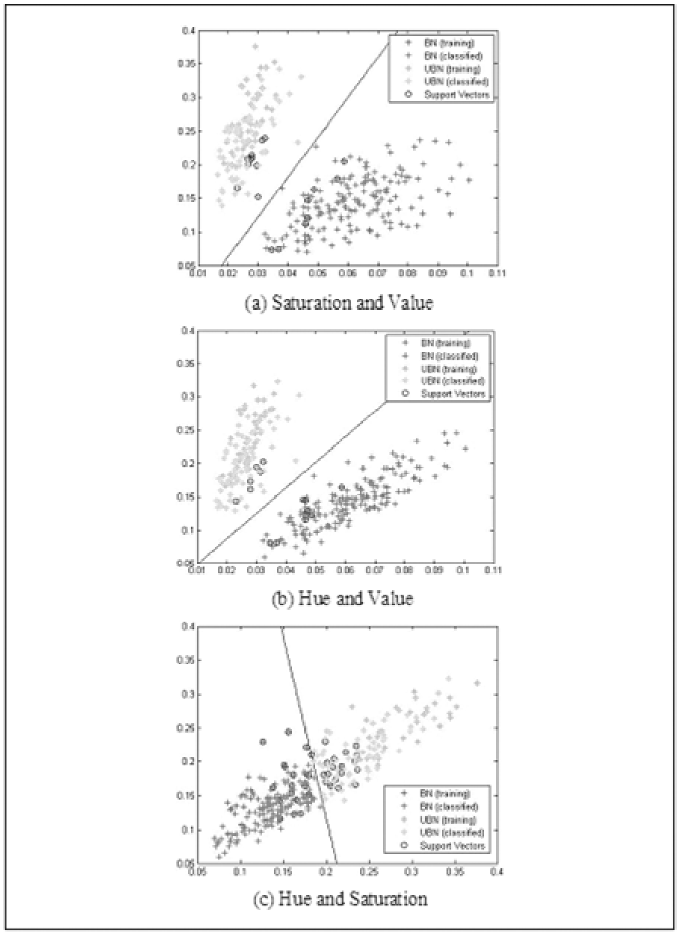


Figure 9: Plot of Mean value of color components of HSV Color Space using SVM classifier.

Chromatic Blue verses Chromatic Red of YCbCr, Hue verses Saturation, and Hue verses Value of HSV color spaces have given success rate of 100% segmentation of arecanut has been done using three.

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