# Classification of Diseased Arecanut based on Texture Features

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## ABSTRACT
In the proposed work, classification of diseased and undiseased arecanut have been determined using texture features of Local Binary Pattern (LBP), Haar Wavelets, GLCM and Gabor. This work has been carried out in two stages. In the first stage, LBP have been applied on each color component of HSI and YCbCr color models and histogram of LBP is generated. The statistical method correlation is used to measure the distance between histogram of training set and query sample and obtained a success rate of 92.00%. We have not achieved better results in the first stage. In the second stage, texture features of Haar wavelets, GLCM and Gabor have been used. In this stage, RGB input arecanut image is transformed to HSI and YCbCr color models and texture features are extracted from each color component. Subset of texture features with high degree of discrimination power has been identified empirically based on combination of texture features. The kNN classifier gave a success rate of 100% for discriminative subset of texture features.

## General Terms
Image Processing, Pattern Recognition, Classification

## Keywords
Arecanut classification, Discriminative Texture Features, Gabor Filters, GLCM, Haar Wavelets, LBP

## 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 of betel-nuts, which form 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 and to the Indians, Indonesians. Betel-nut chewing is as familiar as chewing gum to the Americans V. Raghavan et. al[14]. Arecanut is available in the market with husk and without husk, in this work, arecanut without husk is considered. There might be a diseased arecanut mixed with pure nuts. Diseased nuts should be separated from pure nuts in tender markets. The proposed work will done classification of diseased and undiseased arecanut based on texture features. Human has a major role in classification of these arecanut. This leads to time consuming, expensive for labour and inconsistency in classification. Computer vision based technology is required to address the above problem. There are several computer based technologies for other crops but there is no computer vision based advanced technology to address this problem. We have considered all types of arecanut like Chaali, Bette, Minne, Gotu with diseased and undiseased nuts. Our objective is classification of diseased and undiseased nuts irrespective of the type of arecanut.

In the rest of this paper, we describe literature review briefly in Section 2. The problem is defined in Section 3. Proposed methodology is discussed in Section 4, which includes segmentation using Otsu method. Feature extraction and classification of arecanut using correlation between histograms and kNN classifier. The experimental results and analysis are discussed in Section 5. Finally, conclusions are drawn.

## 2. LITERATURE REVIEW
Zhenhua Guo, Grad. Sch, Zhang, D., Su Zhang in [15], proposed a adaptive LBP (ALBP) using least square estimation to adaptively minimize the local difference for more stable directional statistical features and the statistical features mean and standard deviation used to improve the LBP classification accuracy. Authors have coupled directional statistical features with ALBP, a new rotation invariant texture classification was presented. Li Liu, Fieguth and P.W [7], presented an approach for texture classification based on random projection, suitable for large texture database applications. A small set of random features are extracted from local image patches and those features are embedded into a bag-of-words model to perform texture classification. Suresha M and Ajit Danti in [11], proposed a novel method, in this method a Gabor response co-occurrence matrix (GRCM) is constructed analogous to Gray Level co-occurrence matrix (GLCM). Classification is done using kNN and Decision Tree (DT) classifier based on GRCM features. Zhi-Zhong and Junhai Yong in [16], proposed a texture analysis and classification approach with the linear regression model based on the wavelet transform. This method is motivated by the observation that there exists a distinctive correlation between the samples images, belonging to the same kind of texture, at different frequency regions obtained by 2-D wavelet packet transform. Kandaswamy, U., Adjeroh, D.A. and Lee, M.C. in[6] addressed the problem of efficiency in texture analysis for SAR imagery. It was motivated for the authors by the statistical occupancy model and they have introduced the patch reoccurrences. The approximate features are extracted from GLCM and Gabor wavelets and have given improved results. Dolu, O., Kirtac, K. and Gokmen, M. in[3],ensemble based Gabor nearest neighbour classifier (EGNNC), extends the Gabor nearest neighbor classifier(GNNC), which extracts important discriminative features utilizing both the Gabor filter and nearest neighbor discriminate analysis (NNDA). EGNNC is an ensemble classifier combining multiple NNDA based component classifiers which are designed using different segments of the reduced Gabor features. Mihran Tuceryan and Anil K. Jain in [8], review has done on various aspects of texture features. Authors have discussed on geometric, random field, fractal and signal processing models of extracting textural features from images and also texture processing problems such as

segmentation, classification, and shape from texture are discussed. Authors have summarized possible application areas also.

## 3. PROBLEM DEFINITION

In the proposed work, diseased and undiseased arecanut are considered for classification. At present, classification of diseased and undiseased arecanut has been done by human experts, manually. This type of sorting is rather labour expensive, time consuming and inconsistent. Machine vision technology gives solution to be a replacement of manual sorting in the field of arecanut marketing.

## 4. PROPOSED METHODOLOGY

In the proposed method, arecanut is segmented from a given image using Otsu method. Texture features and a simple kNN classifier have been used for classification. The texture features used in this work are, LBP, Haar Wavelets, GLCM and Gabor features. The attributes used in these texture features are explained in the subsequent sections. Results obtained from each texture feature set and best discriminative subset of features from HSI and YCbCr color models are selected empirically based on combination of features. The below mentioned algorithm discuss about proposed methodology which covers segmentation, feature extraction and classification.

Algorithm

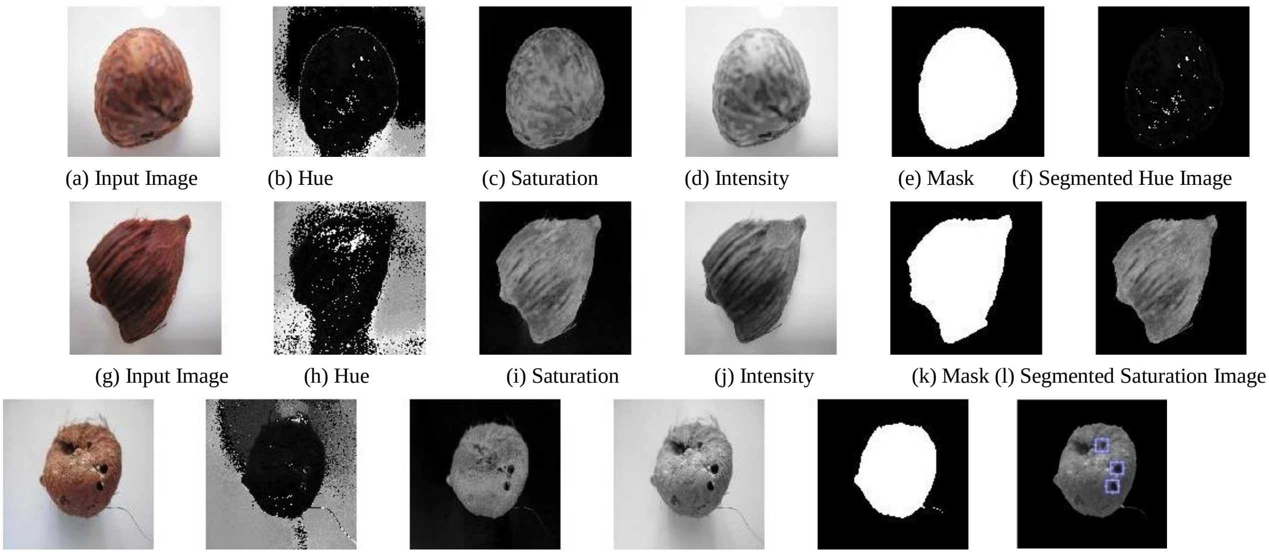
1. Transform a RGB arecanut image to HSI and YCbCr color model.
2. Extract Saturation component from HSI for segmentation of arecanut from background.
3. Threshold based segmentation is used based on Global image threshold using Otsu method.
4. The color components extracted from HSI and YCbCr are Hue, Saturation, Intensity, Yellow, Chromatic Blue and Chromatic red.
5. Enumerate all these color components. Segmented image is multiplied with color component in iteration.
6. From each color component Haar Wavelets, GLCM, Gabor texture features are extracted.
7. Diseased and undiseased arecanut classification has been done using kNN classifier using texture feature set mentioned in step 6.
8. Experimentally, identification of subset of texture features with high degree discrimination power from texture features is mentioned in step 6 based on combinations of features.
9. Classification has been done using kNN classifier with subset of texture features.

### 4.1 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. [10]. The segmented image is converted to binary image and this is called the mask and shown in Fig. 1(e), 1(k), 1(q) and Fig. 2(e), 2(k), 2(q). The mask is multiplied with color components of HSI and YCbCr color models as discussed in the algorithm. The equation for multiplying mask with color component is given in equation (1) and the results are show as in Fig.1 (f), 1(l), 1(r), and Fig.2 (f), 2(l), 2(r).

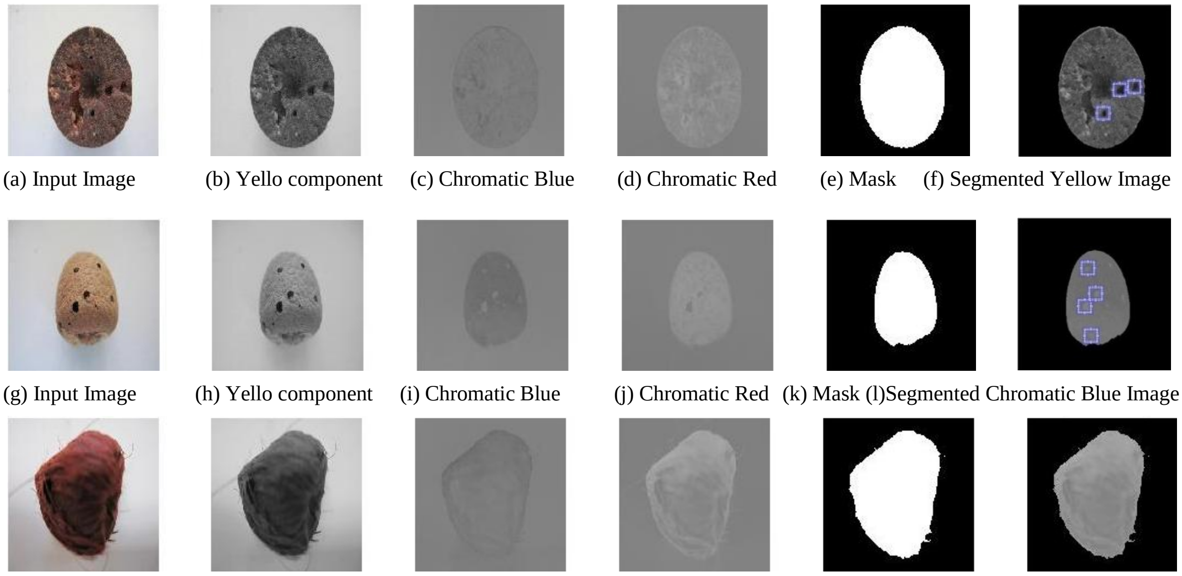
$$F_s(x, y) = \sum_{x=1}^{m}\sum_{y=1}^{n} M(x, y)F(x, y) \quad (1)$$

-where *Fs*, *M* and *F* are the segmented, mask and input images of arecanut respectively. Variables *m* and *n* are spatial sizes of images.



(a) Input Image (b) Hue (c) Saturation (d) Intensity (e) Mask (f) Segmented Hue Image
(g) Input Image (h) Hue (i) Saturation (j) Intensity (k) Mask (l) Segmented Saturation Image
(m) Input Image (n) Hue (o) Saturation (p) Intensity (q) Mask (r)Segmented Intensity Image

**Fig 1: Sample Experimental Results generated from HSI Color Model.**



(a) Input Image (b) Yello component (c) Chromatic Blue (d) Chromatic Red (e) Mask (f) Segmented Yellow Image

(g) Input Image (h) Yello component (i) Chromatic Blue (j) Chromatic Red (k) Mask (l)Segmented Chromatic Blue Image

(m) Input Image (n) Yello component (o) Chromatic Blue (p) Chromatic Red (q) Mask (r) Segmented Chromatic Red Image

**Fig 2: Sample Experimental Results generated from YCbCr Color Model.**

## 4.2 Feature Extraction

The texture features of LBP, Haar Wavelets, GLCM and Gabor Wavelets have been extracted from each color component of HSI and YCbCr color models. Totally 144 texture features are extracted from six color components of the HSI and YCbCr color models.

## Local Binary Patterns

The basic local binary pattern was originally proposed by Ojala et al. [13], was based on the assumption that texture has locally two complementary aspects, a pattern and its strength with the aim of texture classification, and then extended for various fields, including face recognition T. Ahonen [12], face detection A. Hadid [1], facial expression recognition G. Zhao [4] etc. The most attractive advantages of LBP are its invariance to monotonic gray-scale changes, low computational complexity and convenient multi-scale extension. The philosophy behind LBP is simple and well-designed: unify statistical and traditional structural methods. While processing an image, each processing pixel is compared with its eight neighbors and the ones whose intensities exceed the processing pixels are marked as 1, otherwise as 0. In this way we get a simple circular point features consisting of only binary bits. Typically the feature ring is considered as a row vector, and then with a binomial weight assigned to each bit, the row vector is transformed into decimal code for further use. LBP using circular neighborhoods and linearly interpolating the pixel values allows the choice of any radius, *R*, and number of pixel in the neighborhood, *P*, to form an operator, which can model large scale structure. In basic LBP operation threshold value is the processing pixel, this method is noise sensitive, so we choose average of pixels including processing pixel that encompass by an LBP operator as a threshold. Mathematical model for LBP is shown in equation (2).

$$LBP_{P,R}(x,y) = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \qquad (2)$$

-where $g_c$ is the average gray value of the pixels encompass by LBP operator, $g_p$ is the intensity value of pixels in eight neighborhood.

A descriptor for texture analysis is a histogram, *h(i)*, of the local binary pattern shown in equation (3) and its advantage is that it is invariant to image translation.

$$h(i) = \sum_{x,y} B(LBPP, R(x,y) = i) \mid i \in [0, 2^{p-1}],$$

$$B(v) = \begin{cases} 1 & v > T \\ o & otherwise \end{cases} \qquad (3)$$

In order to perform classification of arecanut, each arecanut image in the training and test sets are converted to a spatially enhanced histogram as described the process above. Then the statistical method correlation is used to measure distance between histograms of training set and query sample and the equation for correlation is given in equation (4).

$$Corr(x,y) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(yi - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 (yi - \bar{y})^2}} \qquad (4)$$

-where $\bar{x}$ and $\bar{y}$ are the average intensity values of the histogram *h*. Variables $x_i$ and $y_i$ (where $i$ = 1 to $n$) are the histogram values of training set and test set respectively.

The standard deviation of histogram has been obtained and this feature is used in kNN for classification. The equation for standard deviation is shown in equation (5).

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \qquad (5)$$

-where $x$ is the histogram, $\mu$ is the mean of the histogram and $n$ is the size of the histogram.

***Gabor Features***

Texture analysis using filters based on Gabor functions falls into the category of frequency-based approaches. These approaches are based on the premise that texture is an image pattern containing a repetitive structure that can be effectively characterized in a frequency domain, such as the Fourier domain. One of the challenges, however, of such an approach is dealing with the tradeoff between the joint uncertainty in the space and frequency domains. Meaningful frequency based analysis cannot be localized without bound. An attractive mathematical property of Gabor functions is that they minimize the joint uncertainty in space and frequency. They achieve the optimal tradeoff between localizing the analysis in the spatial and frequency domains Newsam et al., [9].The Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function and it is given by.

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)$$

$$\cos\left(2\pi\frac{x'}{\lambda}+\psi\right) \tag{6}$$

-where $x' = x\cos\theta + y\sin\theta$ and $y' = x\sin\theta + y\cos\theta$ and, $\theta$ represents the wavelength of the cosine factor, $\theta$ represents the orientation of the normal to the parallel stripes of a Gabor function, $\psi$ is the phase offset, $\sigma$ is the Gaussian envelope and $\gamma$ is the spatial aspect ratio specifying the ellipticity of the support of the Gabor function. A filter bank of Gabor filters with various scales and rotations are created. In this work, we have considered with scales of 0, 2, 4 and orientations of 0, 45, 90 and 135. Totally twelve feature vectors were extracted for the above mentioned three scales and four orientations. The corresponding mean ($\mu$) value is determined for each feature vector using the equation (7).

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} \tag{7}$$

-where $x$ is the feature vector and $n$ is the size of feature vector.

***GLCM Features***

Texture feature uses the contents of GLCM to measure the variation in intensity at a pixel of interest. Haralick et al. [5] first proposed in 1973, they characterize texture using a variety of quantities derived from second order image statistics. Co-occurrence texture features are extracted from an image in two steps. First, a pairwise spatial co-occurrences of pixels separated by a particular angle and distance are tabulated using GLCM. Second, the GLCM is used to compute a set of scalar quantities that characterize different aspects of the underlying texture. The GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section Haralick et al., [5]. The GLCM is $N$ x $N$ square matrix, where $N$ is the number of different gray levels in an image. An element $p(i, j, d, \theta)$ of a GLCM of an image represents the relative frequency, where $i$ is the gray level of the pixel $p$ at allocation $(x,y)$ , and $j$ is the gray level of a pixel located at a distance $d$ from $p$ in the orientation $\theta$. While GLCMs provide a quantitative description of a spatial pattern, they are too unwieldy for practical image analysis. Haralick et al., [5] proposed a set of scalar quantities for summarizing the information contained in a GLCM. He originally proposed a total of fourteen features. However, only subsets of these are used Newsam et al. [9]. The following four derived features used in our work are given in Table 1.

**Table 1. Different GLCM Features used in this work**

| | |
|---|---|
| Contrast | $\sum_{i,j} \lvert i-j \rvert^2 \; p(i,j)$ |
| Correlation | $\sum_{i,j} \frac{(i-\mu_i)\;(j-\mu_j)\;p(i,j)}{\sigma_i \;\sigma_j}$ |
| Energy | $\sum_{i,j} p(i,j)^2$ |
| Homogeneity | $\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$ |

***Haar Wavelets Features***

The Haar transformation technique [2] Chin-Chen Chang, Jun-Chou Chuang and Yih-Shin Hu is used to form a wavelet since it is the simplest wavelet transformation method of all and can effectively serve the purpose of feature. In the Haar wavelet transformation method, low-pass filtering is conducted by averaging two adjacent pixel values, whereas the difference between two adjacent pixel values is figured out for high-pass filtering. The Haar wavelet applies a pair of low-pass and high-pass filters to image decomposition first in image columns and then in image rows independently. As a result, it produces four sub-bands as the output of the first level Haar wavelet. The four sub-bands are LL1, HL1, LH1, and HH1. The low-frequency sub-band LL1 can be further decomposed into four sub-bands LL2, HL2, LH2, and HH2 at the next coarser scale as shown in figure 3. LLi is a reduced resolution corresponding to the low frequency part of the image. The other three sub-bands HLi, LHi and Hhi are the high frequency parts in the vertical, horizontal, and diagonal directions respectively. The statistical feature namely energy is derived from the approximation coefficients for each level of decomposition. The features of Haar Wavelets used in this work are given in Table 2.

**Table 2. Haar Wavelets Features used in this work**

| | |
|---|---|
| Mean Value of approximation, horizontal, vertical and diagonal energy | $\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij}$ |
| Mean of Decomposition Vector | $\frac{1}{n}\sum_{i=1}^{n} x_i$ |
| Variance of Decomposition Vector | $\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2$ |
| Entropy of Decomposition Vector | $-\sum_{i=1}^{n} p(x_i)\log_2 p(x_i)$ |

<table>
<tr><td>LL2</td><td>HL2</td><td rowspan="2">HL1</td></tr>
<tr><td>LH2</td><td>HH2</td></tr>
<tr><td colspan="2">LH1</td><td>HH1</td></tr>
</table>

**Fig 3: Two level Haar wavelet decomposition**

***kNN Classifier***

The supervised learning is the most fundamental task in machine learning. In supervised learning, we have training samples and test samples. A training sample is an ordered pair $h_x$, $y_i$, where $x$ is an instance and $y$ is a label. A test sample is an instance $x$ with unknown label. The goal is to predict labels for test examples. kNN classification has two stages; first is the determination of the nearest neighbors and the second is the determination of the class using those neighbors . Let us assume that we have a training dataset $D$ made up of $(x_i)$ $i\epsilon[1,|D|]$ training samples. The samples are described by a set of features $F$ and any numeric features have been normalized to the range [0, 1]. Each training sample is labeled with a class label $y_j \epsilon Y$. An objective is to classify an unknown example $q$. For each $x_i \epsilon D$ can be calculated the distance between $q$ and $x_i$ as follows:

$$d(q, x_i) = \sum_{f \in F} w_f \delta(q_f, x_{i\,f}) \qquad (8)$$

The value of $w_f$ is 1/ (1+$F$), if the feature set $F$ is not normalized to [0, 1]. There are a large range of possibilities for this distance metric; a basic version for continuous and discrete attributes would be:

$$\delta(q_f, x_{if}) = \begin{cases} 0 & f \text{ discrete and } q_f = x_{if} \\ 1 & f \text{ discrete and } q_f \neq x_{if} \\ |\, q_f - x_{if} \,|\, & f \text{ continuous} \end{cases} \qquad (9)$$

The $k$ nearest neighbors is selected based on this distance metric. Then there are varieties 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.

$$Vote(y_j) = \sum_{c=1}^{k} \frac{1}{d(q, x_c)^n} (y_j, y_c) \qquad (10)$$

Thus the vote assigned to class $y_j$ by neighbour $x_c$ is 1 divided by the distance to that neighbour, i.e. $1(y_j , y_c)$ returns 1 if the class labels match and 0 otherwise. In equation (10) $n$ would normally be 1 but values greater than 1 can be used to further reduce the influence of more distant neighbors .

# 5. EXPERIMENTAL RESULTS AND ANALYSIS

The experiment is conducted with the total size of 250 images, among these 60% has been used for training and 40% has been used for testing. The images were taken from Canon Digital camera (Power Shot A1100IS). All the Images were taken to approximately fill the camera field of view in natural day light with white background. Images were resized to 300 X 300 pixel resolution to improve the computation speed. In this method, LBP have been applied on each color component of HSI and YCbCr color models, then histogram was generated. Further distance between the training set and query sample is measured using correlation of histogram and obtained a success rate of 92.00%.

Texture features of Haar Wavelets, GLCM and Gabor Wavelet have been obtained from each color component of HSI and YCbCr color models and the results are shown in Table 3. Best discriminative subset of features has been determined from Haar Wavelets, GLCM and Gabor features empirically based on combination of features. Texture features with high degree of discrimination power has been mentioned in Table 4.

# 6. CONCLUSIONS

In this paper, LBP with histogram correlation has given a success rate of 92.00, so this method has not achieved better results, so next we have used texture features of Haar Wavelets, GLCM and Gabor are extracted from each channel of HSI and YCbCr color models that have given total of 144 features and dimension of these features were reduced into subset of features with high degree of variance. This subset of features was identified empirically based on combination of features.

**Table 3. Results obtained for Different Texture Features**

| **Features** | **Success Rate in %** |
|---|---|
| LBP | 92.00 |
| Haar Wavelets | 92.30 |
| GLCM | 84.61 |
| Gabor | 98.00 |
| Combinations of best discriminative subset of features | 100.00 |

**Table 4. texture features with high degree of discrimination power**

| **Image Component** | **Texture Features** |
|---|---|
| Intensity component from HSI color model | Contrast, Correlation, Energy and Entropy of GLCM |
| Yellow Component from YCbCr color model | Vertical and diagonal approximation features of Haar Wavelets |

In this work, disease for arecanut that comes after processing only considered. Diseases that come before processing can be considered in future work. This can be a base paper to determine some other diseases of arecanut and early detection of disease that comes when nut is growing in areca tree. This work can be extended to identify disease of fruits, flowers and seeds etc.

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