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# Invariant of Rotation and Scaling for Classification of Arecanut Based on Local Binary Patterns

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***Abstract— The Local Binary Pattern (LBP) operator is a powerful means of micro texture description that has been used in texture analysis of arecanut in this work. The Gabor filters and GLCM (Gray Level Co occurrence Matrix) will capture data with different scale and angle. The Gabor and GLCM based LBP has been used for classification of arecanut data. In the proposed method, LBP has been applied on arecanut image then Gabor filters and GLCM have been applied on LBP. These Gabor filters and GLCM texture features of arecanut have been extracted for classification. The images are normalized to 300x300 sizes in order to improve the processing time. The results are compared and discussed with Histogram correlation, GLCM, Gabor, combined (Gabor-GLCM) features. The kNN classifier has given good success rate for combined features.***

***Keywords— Arecanut classification; Correlation; Gabor Filters; GLCM; Histogram; kNN; LBP; Texture Features;***

## I. INTRODUCTION

Arecanut is largely cultivated in the plains and foot hills of Western Ghats and western regions of India. Arecanut is also called betelnut or supari in India. It is used in India and other south countries as a masticatory. Chaali nuts are one of the types of the arecanut; it is covered with husk as shown in Fig. 2(a) and 2(e). Currently, the husk is being removed with machines. This process will be repeated until the husk has been removed completely as shown in Fig. 2(i) and 2(m). In this process, human has a major role in classification. This leads to time consuming and inconsistency. Computer vision based technology is needed to address the above issue. There are several computer based technologies for other crops but still there is no computer vision based advanced technology for classification of arecanut. Recent work in feature-based classification has focused on non-parametric techniques that can classify samples. The kNN classifier is one of the most popular choices for learning and reasoning from feature-based examples. Many machine learning systems have been developed for using kNN classifier from collection of samples. There are two types of arecanuts considered for this work, namely Chaali and Nice Idi. In the proposed method, arecanuts are classified using LBP, histogram matching, LBP-Gabor features, LBP-GLCM features like Contrast, Correlation, Energy and Homogeneity. We have conducted a survey and collected samples from agricultural fields and tender markets. In the rest of this paper, we describe literature review briefly in Section II. The problem is defined in Section III. Then, presented our proposed methodology in Section IV, that includes segmentation using threshold based segmentation, feature extraction and classification of arecanuts using histogram correlation and kNN classifier, and experimental results and analysis are discussed in Section V. Finally, concluded the paper in Section VI.

## II. LITERATURE REVIEW

Ajit Danti and Suresha in [2], proposed a technique for classification of arecanut based on texture features. Classification is done using Mean around features, Gray level co-occurrence matrix (GLCM) features and combined (Mean around-GLCM) features. Decision trees classifier is used for classification of arecanut in to six classes. Proposed method is experimented on data set of size 2214 using cross validation and found success rate of 98.37% for GLCM features, 98.28% for Mean around features and 99.00% for combined features. Xu Xianchuan and Zhang Qi in [16] proposed a novel medical image retrieval method, local binary pattern with image Euclidean distance, which takes into account the spatial relationships of pixels, and it is robust to small perturbation of images. Their experiments showed that image Euclidean distance improved the performance of standard LBP algorithm. Meena, K, Suruliandi, A in [7] investigated performance evaluation of LBP and its modified models, Multivariate Local Binary Pattern (MLBP), Center Symmetric Local Binary Pattern (CS-LBP) and Local Binary Pattern Variance (LBPV). The researchers were conducted experiments on JAFFE female, CMU-PIE and FRGC version 2 databases and their results shows CS-LBP performs better than the remaining other models. Lin, C.-H., Liu C.-W., Chen H.-Y in [6] proposed an adaptive local binary patterns histogram (ALBPH) and gradient for adaptive local binary patterns (GALBP) for image retrieval and classification. They have used colour and greyscale images to generate a variety of image subsets. The authors discovered that the proposed feature extraction method can effectively describe the texture characteristics of images. Meiru Mu, Qiuqi Ruan, Yongsheng Shen in [8] proposed a novel discriminative local binary patterns statistic (DLBPS) for palmprint recognition. In this approach, a palmprint is divided into non-overlapping and equal sized regions and labelled these with LBP. The Discriminative Common Vectors (DCV) was applied for dimensionality reduction. kNN classifier was used for classification. Shu Liao, Chung, A.C.S in [12] proposed a new feature extraction method. They have introduced a concept of advanced local binary patterns (ALBP), which gives local dominant structural characteristics of different kinds of textures. The global spatial distribution features of the ALBP were extracted by ALBP with aura matrix measure as the second layer. The proposed approach has been compared with other widely used texture classification techniques and evaluated by applying classification tests to randomly rotate and histogram equalized images in Brodatz and CUReT texture databases. Pereira E.T, Gomes H.M, de Carvalho, J.M. in [10] proposed a new feature extraction approach that combines Integral Histograms and LBP, this novel approach is called the Integral Local Binary Patterns (INTLBP) for face/non-face classification. Wenchao Zhang Shiguang Shan, Xilin Chen, Wen Gao in [15] proposed a Kullback-Leibler divergence (KLD)-based LGBP for partial occluded face recognition. The local property of LGBP face recognition is used in the method, by introducing KLD between the LGBP feature of the local region and that of the non-occluded local region to estimate the probability of occlusion. The probability is used as the weight of the local region for the final feature matching. Guang Han, Chunxia Zhao in [4] improved multi-channel local binary patterns (LBP) in RGB color space are used as textured color features and a kNN is employed for visual training and classification.

## III. PROBLEM DEFINITION

In this work, two types of arecanut are considered for classification. Qualitative sorting is usually performed manually. This type of evaluation is rather expensive and inconsistency. Machine vision technology gives solution for all these problems and it is considered to be a replacing the manual sorting in the field of arecanut marketing.

## IV. PROPOSED METHODOLOGY

In the proposed method, arecanuts are segmented from the given image using threshold based segmentation. In feature extraction stage, LBP have been applied on an image and image histogram, Gabor filters and GLCM have been applied on LBP as shown in Fig. 1.

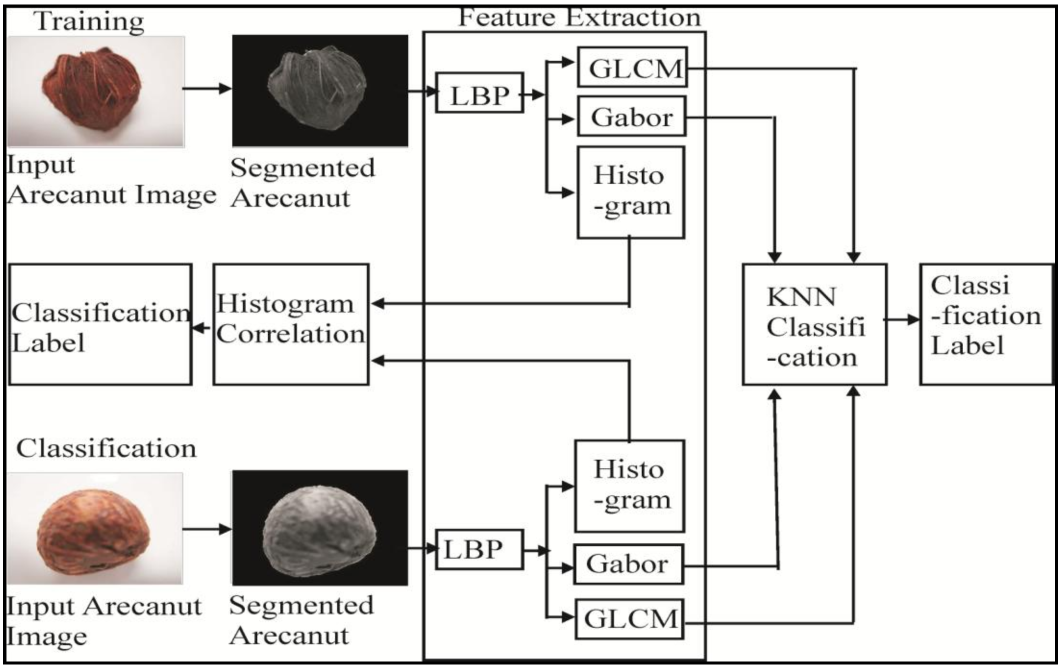


Fig. 1. Block Diagram of the Proposed Methodology

### A. Segmentation

The first step in arecanut classification is to segment a arecanut from background. The process of segmentation subdivides an image into its constituent parts or objects. The level to which this subdivision is carried 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. Threshold based segmentation has given good segmentation results for arecanut. The major idea used in segmentation in this work is, a color image is converted into HSV image and saturation channel has been used for threshold based segmentation based on dynamic thresholding Rafael C. Gonzalez et al. [11]. The segmented image is converted into binary image and this is called the mask as shown in Fig. 2(c), 2(g), 2(k) and 2(o). The mask has been multiplied with the gray scale image of the input image using equation (1) and the results are show as in Fig. 2(d), 2(h), 2(l), and 2(p).

$$f_s(x,y) = \sum_{x=1}^{M} \sum_{y=1}^{N} m(x,y)\, f(x,y) \quad (1)$$

-where $f_s$, $m$ and $f$ are the segmented, mask and input grayscale images respectively. $M$ and $N$ are the size of image.

 

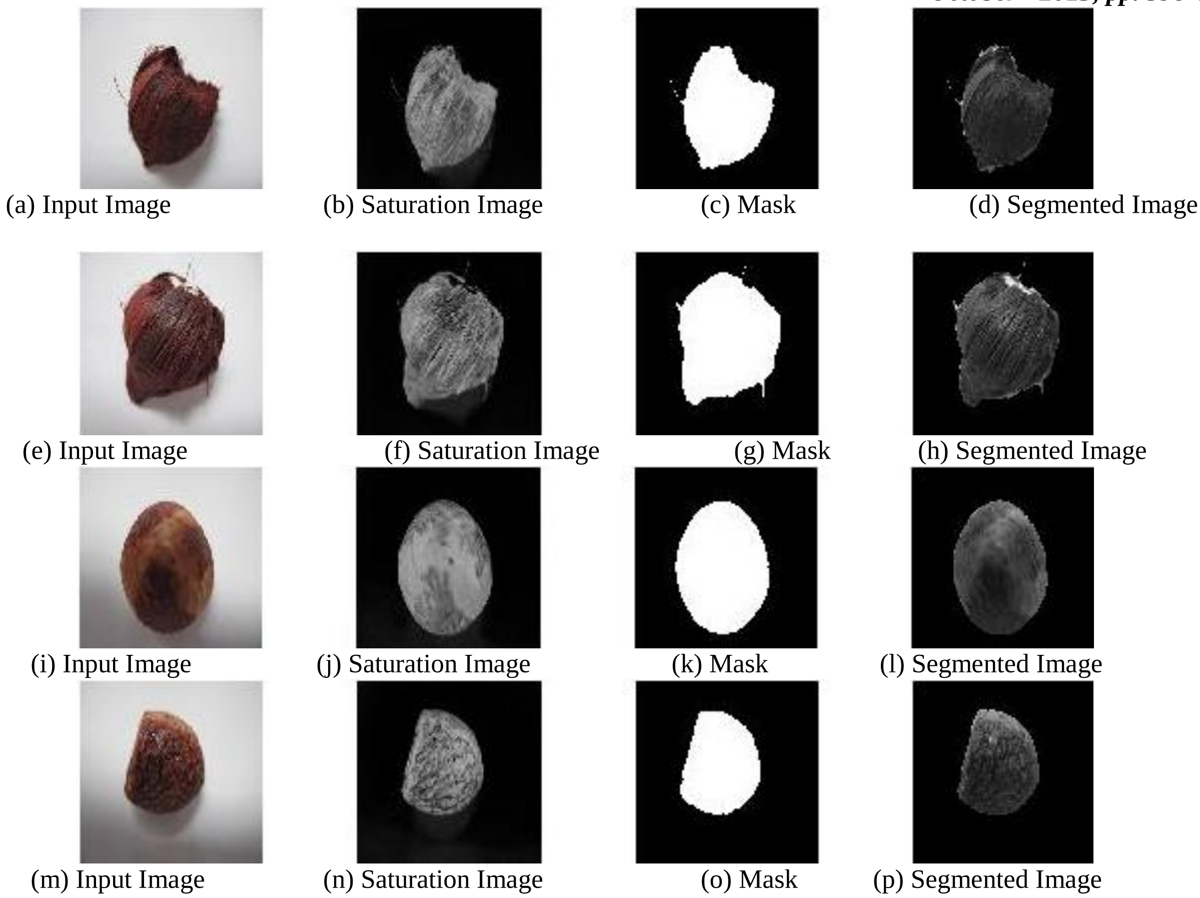


Fig. 2. Sample Experimental Results.

### *B. Feature Extraction*

In the feature extraction stage, LBP have been applied on arecanut. The histogram, Gabor wavelets and GLCM features are extracted from LBP. The GLCM features such as Contrast, Correlation, Energy and Homogeneity based on intensity of pixels have been determined.

#### *1) Local Binary Patterns*

The basic local binary pattern was originally proposed by Ojala et al. [14], 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 [13], face detection A. Hadid [1], facial expression recognition G. Zhao [3] 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. In Fig. 3, given an illustration for how LBP serves as local descriptor. Each neighbor pixel is compared with the center pixel, and the ones whose intensities exceed the center 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. An illustration of the basic LBP operator is shown in Fig. 3 and the corresponding equation is shown in equation (2).

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

-where $g_c$ is the gray value of the central pixel, $g_p$ is the value of its neighbors.

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.

$$h(i) = \sum\nolimits_{x,y} B(LBPP, R(x,y) = i) \mid i \in [0, 2^{p-1}],\ B(v) = \begin{cases} 1 & v > T \\ o & otherwise \end{cases} \tag{3}$$

In order to perform classification of arecanut, each arecanut image in the training and test sets are converted to a spatially enhanced histogram via the process described above. Then ordinary nearest neighbor classification is performed with a histogram distance measure. In this work, correlation has been used to measure distance between histograms and is given in equation (4).

 

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

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

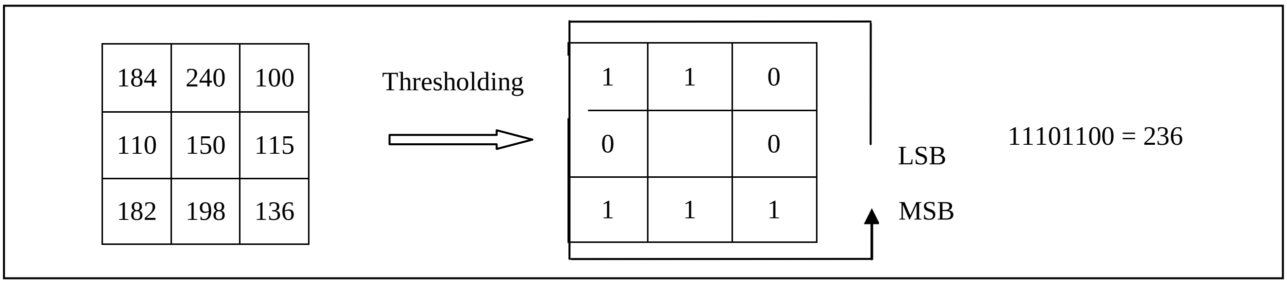


Fig. 3. Basic Working Principle of LBP Operator.

*2) 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.

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \psi\right) \quad (5)$$

-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 is created. In this work, we have considered with scales of 0, 2, 4 and orientations of 0, 45, 90 and 135.

*3) GLCM Features*

Texture feature uses the contents of GLCM to measure a 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, the 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 binary codes obtained by local thresholding of LBP are transformed into decimal codes. An element $p(i, j, d, \theta)$ of a GLCM of an image represents the relative frequency, where $i$ is the decimal value of the pixel $p$ at allocation $(x, y)$ , and $j$ is the decimal value 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 I.

TABLE I: DIFFERENT GLCM FEATURES

| | |
|---|---|
| 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 | $\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$ |

*4) 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; 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 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:

$$d(q, x_i) = \sum_{f \in F} w_f \delta(q_f, x_{if}) \tag{6}$$

There are a large range of possibilities for this distance metric; a basic version for continuous and discrete attributes would be:

$$\delta(q_f, x_{if}) = \begin{cases} 0 & f \text{ discrete and } q_f = x_{if} \\ 1 & f \text{ discrete and } q_f \neq x_{if} \\ |q_f - x_{if}| & f \text{ continuous} \end{cases} \tag{7}$$

The $k$ nearest neighbours is selected based on this distance metric. Then there are a variety of ways in which the $k$ nearest neighbours can be used to determine the class of $q$. The most straightforward approach is to assign the majority class among the nearest neighbours 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 neighbours get to vote on the class of the query case with votes weighted by the inverse of their distance to the query.

$$Vote(y_j) = \sum_{c=1}^{k} \frac{1}{d(q, x_c)^n} (y_j, y_c) \tag{8}$$

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 (8) $n$ would normally be 1 but values greater than 1 can be used to further reduce the influence of more distant neighbours.

## V. EXPERIMENTAL RESULTS AND ANALYSIS

The experiment is conducted with total of 256 images. Among these 60% have been used for training and 40% have been used for testing. These results are accepted by agricultural experts. 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 the proposed method, LBP have been applied then Gabor filters, GLCM and Histogram matching have been applied on LBP. The kNN classifier has been used for classification for the Gabor and GLCM features. The Histogram correlation gave a success rate of 87.15%, LBP-Gabor filters and LBP-GLCM features have given a good success rate for different k values as shown in Table II.

TABLE II:
SUCCESS RATES AGAINST DIFFERENT K VALUES FOR LBP BASED GLCM, GABOR AND GLCM-GABOR FEATURES

| **k Value** | **Success Rate in %** | | |
|---|---|---|---|
| | **LBP-Gabor** | **LBP-GLCM** | **LBP-Gabor-GLCM** |
| 3 | 72.47 | 86.23 | 94.49 |
| 7 | 77.98 | 87.15 | 90.82 |
| 11 | 73.39 | 87.15 | 89.90 |
| 15 | 66.97 | 87.15 | 88.07 |
| 19 | 65.13 | 87.15 | 81.65 |
| 23 | 66.05 | 86.23 | 79.81 |
| 27 | 65.13 | 88.99 | 77.98 |
| 31 | 65.13 | 87.15 | 73.39 |
| 35 | 65.13 | 88.99 | 72.47 |
| 39 | 65.13 | 88.07 | 71.55 |
| 43 | 65.13 | 88.07 | 71.55 |
| 47 | 65.13 | 88.99 | 67.88 |

 

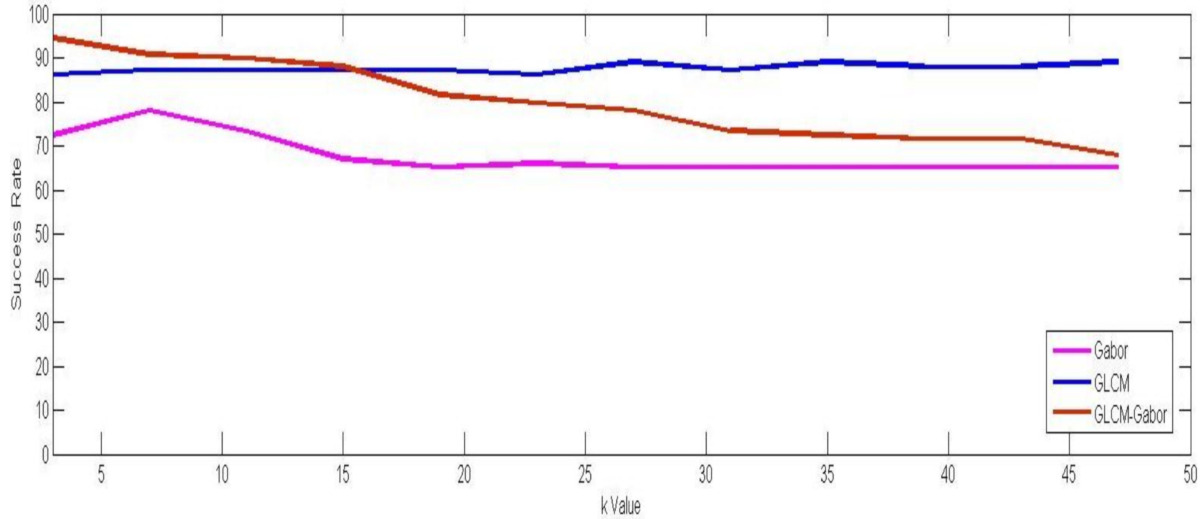


Fig. 4. Plot of success rate for LBP-GLCM, LBP-Gabor and LBP-GLCM-Gabor features against different k values

## VI. CONCLUSIONS

In this paper, RGB images have been converted to HSV image. The saturation channel was extracted for segmentation. The threshold based segmentation has given a good segmentation results. The LBP have been applied for the arecanut images. Image histogram, Gabor, GLCM features have been extracted from LBP. First, classification has done with histogram features with correlation distance metric and then, classification has been done with Gabor, GLCM and combined (GLCM-Gabor) features extracted from LBP using kNN classifier. Empirical results show that combined features gave optimum results when the k value is 3. The success rate decreases as the k value decreases and is shown in Fig. 4.

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