# Color and Texture in Classification of Coconut

**Siddesha S, S K Niranjan**

***Abstract***: ***Coconut is one of the commercial and versatile crops and is a part of day to day food in India. Classification of coconut is a process of separating the nuts based on its maturity. In this paper, we proposed a model for classifying the nuts by color and texture features. SVM is used as a classifier for classifying nuts into three separate classes, tender coconut (TC), mature coconut (MC) and Copra (CP). All these classes are used for different purposes and occasions. Color histogram and color moments are used as color features with wavelet, LBP, GLCM and Gabor features as texture features. Experimentation is conducted on a data set of 900 images with combination of color and texture features using SVM as classifier. In classification part, we used two SVM approaches One-Against-One and One-Against-All with four different kernel functions namely, linear, quadratic, polynomial and radial based. An accuracy of 99.07% is attained with the combination of color moments and Gabor using One-Against-All SVM for linear kernel function.***

*Index Terms*: **Coconut, Color, Texture, SVM.**

## I. INTRODUCTION

Coconut is one of the traditional, commercial and plantation crops of India. It is used for wide variety of food in day to day life. It is very difficult to assume Indian food without coconut. India stands first in the production and consumption of coconut. Each and every part of coconut is used for different purposes. This also created business opportunities to set up industries, which created employment. As per the Indian mythology, the coconut tree is well known as Kalpavriksha means a tree which can give anything asked.

There are some works reported in the literature on classification and grading of different crops using computer vision and machine learning techniques. A method was reported for auto classification of arecanut based on different features, such as color, texture and shape [1]. In another work, a two class classification system was built using color as a feature. This work has three parts, segmentation, masking and classification. They considered YCBCR image with 3 sigma control limits for segmenting, and used red and green components from the segmented region for classification [2]. A work proposed for classification arecanut using decision tree classifier by considering texture features using GLCM and mean around features [3].

Also few works have been reported for arecanut grading. In one of the work, a two grading system was proposed for grading boiled and non-boiled arecanut. Here first segmentation is carried out using 3 sigma control limits considering color features, then the segmented arecanut is classified using support vector machine(SVM) for classification [4]. In another work, a system was built for detection and classification of quality in arecanut by combining the image processing techniques and neural networks. The defective arecanut was segmented using detection line (DL) with 3 color and 6 geometric features. Later the defective areas were classified using back propagation neural network for sorting the quality [5].

A work was reported with Artificial Neural Network (ANN) for categorization of oil palm fresh fruit bunch based on their ripeness. The extracted color features were put to ANN for learning. They used independent test data for measuring the performance of the network [6]. Machine vision techniques were for grading of fruits and developed a system for the online estimation of the quality of Oranges, Peaches and Apples, and evaluated the efficiency of the techniques using size, colour, stem location and detection of external blemishes as quality attributes [7]. A system was developed for classifying the citrus fruits by identifying most common defects using multi spectral computer vision [8]. Another system was developed for automatic extraction of fruit quality feature for a date fruit [9].

A study was reported for testing the feasibility of spectral mixture model by using it for capturing the land coverage maps of coconut. The final results from spectral mixture analysis (SMA) were measured by comparing with the set of ground truth data. The result achieved with an accuracy of 87% [10]. Another system was developed for classifying the leaf rot disease affected coconut tree leaves by a new feature distance measure of end points considering the line moving in the leaf with neural network as classifier [11].

## II. PROPOSED METHODS

The proposed work aims at classifying the coconuts in to three classes like Tender Coconut (TC), Mature Coconut (MC) and Copra (CP).The model has two stages, feature extraction and classification shown in figure 1. The first stage is for extracting the features of the given image. Here we used two different features color and texture for the classifying the coconut images. In color feature we used two different methods color histogram and color moments. For extracting texture we used four different methods wavelets, local binary pattern (LBP), gray level co-occurrence matrix (GLCM) and Gabor. In the second stage the extracted features are used for classifying the coconuts into respective class. We used two approaches of SVM, One-Against-One and One-Against-All. Also four different kernel functions linear, quadratic, polynomial (with degree=3) and radial basis function (with sigma=5) to check the impact of these kernel over the classification accuracy. Experimentation is conducted over an image dataset of 900 images of 300 images per class across three shown in figure 2.

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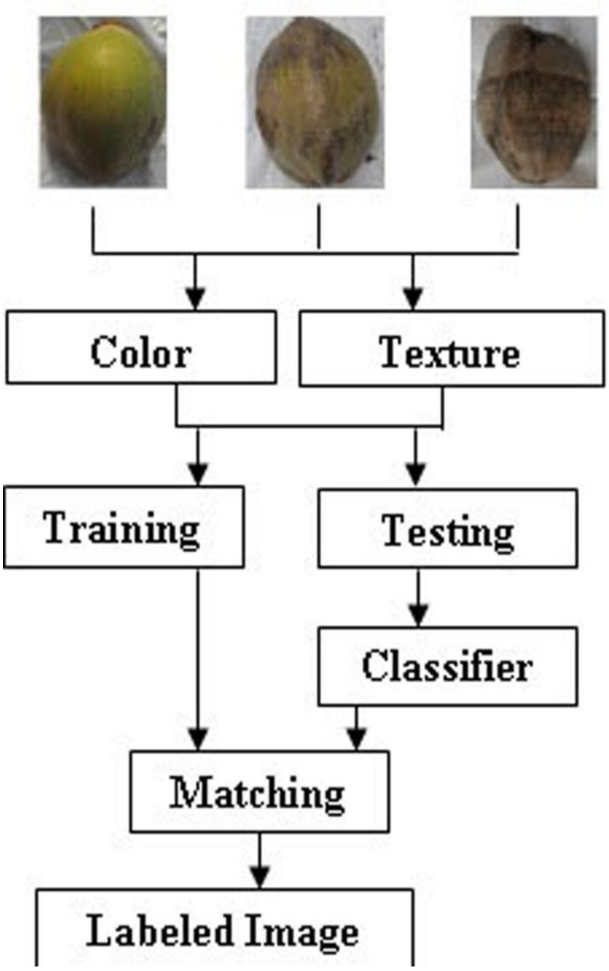


**Fig. 1. Proposed model for colour and texture based classification**

## A. Color features

The Color features are the most commonly used features as it is perceived by the human eye while viewing an image. Also color helps in discriminating one image with other easily. This feature is very sensitive for human vision and thus this is considered as one of the important feature while extracting the feature in recognition and classification applications. There are different color spaces used before extracting the color features like RGB, CIE, Lab, HIS etc. Among these RGB color space is most commonly and widely used while considering computer based images as it uses combination of primary colors red, green and blue.

### Color Histogram

The representation of distribution of different colors of an image is known as color histogram. It represents the density of each color pixel present in the fixed list of colors of an image. Color histograms are easy to compute, and they are invariant to rotation and translation of image content. Color histograms are formed based on the set of bins, with every single bin represents distribution of pixels of an image for a specific color [12], [13], [14]. Color histogram of an image can be defined as a vector,

$$C_H = \{C_H[0], C_H[1], ......, C_H[i], ....., C_H[k]\} \quad (1)$$

Where $i$ - is a color of the color histogram in the RGB color space, $C_H[i]$ - is the number of pixels of a color $i$ of the given image, $k$ – is the total number of bins of the color histogram.


**Fig. 2. Three classes of coconut.**

### Color moments

Even though color histogram is a simple method, it has quantization effect. To avoid this, a color moment technique is proposed by [15]. The color moments method is a widely used feature for color based retrieval because of its simplicity and effectiveness [16], [17], [18]. Moments will be used for characterization of probability distribution. Probability distribution can be used for interpreting the color distribution of a given image. The lower order moments have the color distribution information and can be captured using first four moments, i.e., mean, variance, skewness and kurtosis. These moments are effective in color representation due to their good approximation criteria [16]. Here the moments defines the the $i^{th}$ color channel at the $j^{th}$ image pixels as $P_{ij}$ and the four moments,

**Mean**- Represents the average color of the image and is given by,

$$M_i = \sum_{j=1}^{K} \frac{1}{K}\left(P_{ij}\right) \quad (2)$$

**Standard Deviation**- Is the square root of variance which represents the distribution of color in an image and is calculated by,

$$\sigma_i = \sqrt{\frac{1}{K}\left(\sum_{j=1}^{K}\left(P_{ij} - M_i\right)^2\right)} \quad (3)$$

**Skewness**- Provides the nature of asymmetric color distribution which in term used for finding the shape of the distribution and represented by,

$$S_i = \sqrt[3]{\left(\frac{1}{K}\sum_{j=1}^{K}\left(P_{ij} - M_i\right)^3\right)} \quad (4)$$

**Kurtosis**- This is similar to skewness and computes the color distribution shape, specifically measures the peakedness or flatness of the distribution relating to its normal distribution and is computed by,

$$K_i = \sqrt[4]{\left(\frac{1}{K}\sum_{j=1}^{K}\left(P_{ij} - M_i\right)^4\right)} \quad (5)$$

### B. Texture features

These features are the important features used in computer vision applications. This helps in image partition into different regions which will be then classifies the regions. Various methods are used for extraction of texture from the image. In this work we used four different methods for extraction of texture namely; wavelet, local binary patterns (LBP), gray level co-occurrence matrix (GLCM) and Gabor techniques.

#### Wavelet features

Wavelet is very useful in the analysis of multi resolution by considering both space and frequency [19]. Wavelet transforms are useful in avoiding issues with frequency and time resolution properties. The basic wavelet transform is in facilitating time-frequency representation. The two dimensional wavelet functions based on scaling and translation are given by,

$$\varphi_{i,j,k}(x,y) = 2^{\frac{i}{2}}\,\varphi\left(2^i x - j, 2^i y - k\right) \quad (6)$$

$$\psi_{i,j,k}^{m}(x,y) = 2^{\frac{i}{2}}\psi^m\left(2^i x - i, 2^i y - j\right) \quad (7)$$

Where $m = \{h, v, d\}$ and $m$ is directional wavelets $\psi^h(x,y), \psi^v(x,y)$ *and* $\psi^d(x,y)$ in horizontal, vertical and diagonal direction [19]. In this work we used 9 wavelet texture features which forms the energy co-efficient for horizontal, vertical and diagonal wavelets of level 3, given by,

$$E^h = \sqrt{\sum\left(\psi^h(x,y)\right)^2 / 255} \quad (8)$$

$$E^v = \sqrt{\sum\left(\psi^v(x,y)\right)^2 / 255} \quad (9)$$

$$E^d = \sqrt{\sum\left(\psi^d(x,y)\right)^2 / 255} \quad (10)$$

#### Gabor features

Gabor features are capable of analyzing the variation in intensity of image locally and facilitates multi-resolution by accomplishing both frequency and position. This is similar to short term Fourier transforms and effectively analyzes the time-frequency of varying wave signal qualities. The Gabor filter extracts the texture elements of an image by considering their orientation and scaling using the tunable edge and line indications. The elements extracted from the region are used for describing the texture information [20]. A two dimensional Gabor function $f(m,n)$ and its Fourier transform $F(x,y)$ is given by,

$$f(m,n) = \left[\frac{1}{2\pi\sigma_m\sigma_n}\right] exp\left[-\frac{1}{2}\left[\frac{m^2}{\sigma_m^2} + \frac{n^2}{\sigma_n^2}\right] + \frac{2}{P_{ij}}W_x\right] \quad (11)$$

$$F(x,y) = \exp\left\{-\frac{1}{2}\left[\frac{(x-W)^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right]\right\} \quad (12)$$

Where $\sigma_x = \frac{1}{2\pi\sigma_m}$ *and* $\sigma_y = \frac{1}{2\pi\sigma_n}$.

#### Local binary pattern (LBP)

LBP operator is the gray scale operator and is rotation invariant in nature. It is working on spatial structure of the image by differentiating the local image texture [21]. To achieve invariance of a gray scale, it assigns a unique pattern label to each pixel of the image and compares pixel value with the binary pattern of its neighbors and is computed by,

$$L_{P,R} = \sum_{p=0}^{P-1} t(g_n - g_c)2^P \quad (13)$$

Where $t(g_n - g_c) = \begin{cases} 1, & (g_n - g_c) >= 0 \\ 0, & (g_n - g_c) < 0 \end{cases}$

#### Gray level co-occurrence matrix (GLCM)

GLCM calculates the texture feature used to measure the intensity of the interested pixel of the image [12]. The texture of the image is characterized by different second order statistical quantities. It has two stages in extraction of texture features; first one separates the spatial paired co-occurrences with particular angle and distance. The second stage various aspects of the texture is computed by characterizing the set of scalar quantities using GLCM, which is a $M \times M$ matrix with $M$ number of various gray levels of the image. The GLCM of an image, the relative frequency represented with i as the gray level of and a pixel at $(x,y)$, and $j$ is the pixel gray level at the distance of d from pixel p having a orientation $\theta$ given by $p(i,j,d,\theta)$. Five subset features of GLCM correlation, contrast, energy, entropy and homogeneity are considered and

are given by $\sum_{i,j}\frac{(i-\mu_i)(j-\mu_j)\vec{p}(i,j)}{\sigma_i\sigma_j}$, $\sum_{i,j}|i-j|^2 p(i,j)$,

$\sum_{i,j} p(i,j)^2$, $\sum_{i,j=0}^{N-1} -ln(P_{i,j})P_{i,j}$ *and* $\sum_{i,j}\frac{p(i,j)}{1+|i-j|}$

respectively.

### C. Classification

A method of separation of the classes with similarities


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based on the combination of color and texture features. This determines the belonging of unknown sample arecanut image to a finite class which is defined physically. Here we used Support Vector Machine (SVM) classifier for classifying the three classes of coconut. Two different approaches of SVM One-Vs-One and One-Vs-All are used with different kernel functions linear, quadratic, polynomial and radial basis.

Multiclass pattern recognition problems are generally addressed using the method of voting, which combines many binary classification functions [23], [25].

### Support Vector Machine (SVM)

A Support vector machine (SVM) is one the supervised learning algorithm used for classifying the two class problem by separating hyperplane. This algorithm results with an effective hyper plane for new sample based on labeled training samples. For a space with two dimensions the hyperplane is a line which separates the plane into two parts with each class [23]. SVMs are extensively used for classification and regression problems [24], [28]. These are of linear in nature [29].

### One-Against-One

To solve an $m$ - class problem is by considering a number of binary classifiers and a totally $m$ binary classifiers considered with $m^{th}$ classifier creates a hyperplane by separating class $N$ and the $m-1$ other classes. There are $(m(m-1)/2)$ total hyper planes will be created for dividing each class from other classes [30], [31].

### One-Against-All

This approach is the most common approach for multi class classification with SVM. For solving $m$ - class problem it creates $m$ hyperplanes, where each one is framed by using all training samples [30], [31].

### Kernel functions

A kernel is a mathematical function used in SVM classification for organizing the input data into a specific format i.e. for making a non linear decision surface to linear space with high dimension. This helps for deciding creating of hyperplane for separating the classes. There are different kernels used in SVM. In our work we used four different types of kernels namely, linear, quadratic, polynomial and radial based function. Linear kernel separates the samples using a straight hyper plane. This gives good result in case of linearly separable cases by classifying two classes at a time. Mapping of data points to higher dimension is not required. Polynomial Kernel is most commonly used with SVM. This is normally works well with data which is non separable. Quadratic kernel is nothing but the second order polynomial kernel commonly used in specific applications like speech recognition.

Radial basis function kernel- This kernel is most commonly used with SVM when dealing with classification of sample which not linearly separable. This can be adjusted as per the sample by varying its sigma value [32], [33].

## III. EXPERIMENTATION AND DISCUSSION

Dataset is very essential for any computer vision and machine learning work. In order to carry out the experimentation, we created our own coconut image data set contain a total of 900 images across three classes, i.e., 300 images per class. NIKON COOLPIX L810 Digital camera with 26X Zoom used for capturing the image with a distance of one meter approximately. The images were captured from different coconut farms located in and around Mysuru, Karnataka. Two types of features were extracted namely color and texture. The color features used are color histogram and four color moments (mean standard deviation, skewness and kurtosis). The different texture features extracted are wavelet, Gabor, LBP and GLCM. In order to distinguish with one coconut class with other only color feature is not sufficient, so we used the combination of color and texture features. We experimented on eight different combinations of color and texture features (Histogram, Wavelets), (Histogram, Gabor), (Histogram, LBP), (Histogram, GLCM), (Moments, Wavelets), (Moments, Gabor), (Moments, LBP), (Moments, GLCM). Total number of features used in each combination is given in Table 1. The classification is carried out using SVM by varying training from 10% to 70%. Here we used two different approaches One-Against-One and One-Against-All with four kernels functions linear, quadratic, polynomial and radial basis function to study their impact on the classification accuracy shown in figures 3 to 6. The final results are in Table 2 to Table 5 for texture features with color histogram and color moments features. Results of color histogram and Gabor features with SVM One-Against-One and One-Against-All for four kernel functions with 40% training is shown in figures 7 to 10. For training percentage from 10% to 30% the classification accuracy was increasing and at 40% it has a good accuracy, increasing the training percentage from 50% to 70% classification accuracy was decreasing. A classification accuracy of 99.07% is achieved for the combination of Color moments and Gabor with One-Against-All SVM for linear kernel function with 40% training and the corresponding confusion matrix are given in Table 6.

Table 1. Number of features used in each combination

| Sl. No | Color features | | Texture features | | Total No. of features |
|---|---|---|---|---|---|
| | Feature | No. of features | Feature | No. of features | |
| 1 | Histogram | 27 | Wavelet | 36 | 63 |
| 2 | Histogram | 27 | LBP | 256 | 283 |
| 3 | Histogram | 27 | GLCM | 12 | 39 |
| 4 | Histogram | 27 | Gabor | 216 | 243 |
| 5 | Moments | 12 | Wavelet | 36 | 48 |
| 6 | Moments | 12 | LBP | 256 | 268 |
| 7 | Moments | 12 | GLCM | 12 | 24 |
| 8 | Moments | 12 | Gabor | 216 | 228 |

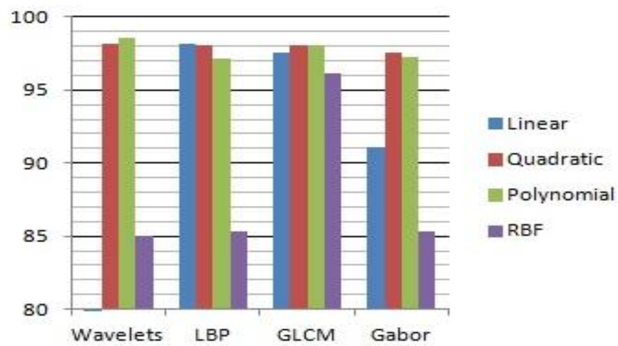


**Fig. 3. Classification accuracy for color histogram and other textures with 4 kernel**


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**functions for 40% training using SVM with One-Against-One approach.**

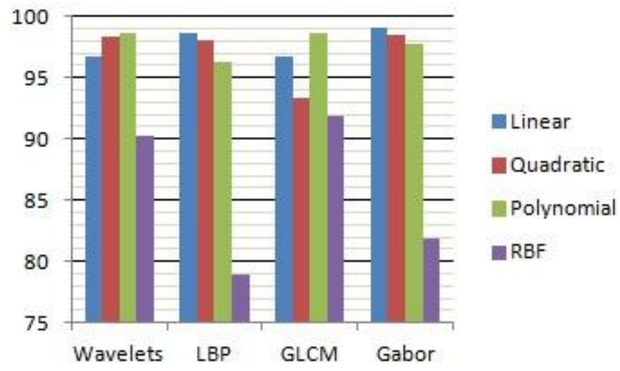


**Fig. 4. Classification accuracy for the combination of color histogram and other textures with 4 kernel functions for 40% training SVM with One- Against-All approach.**

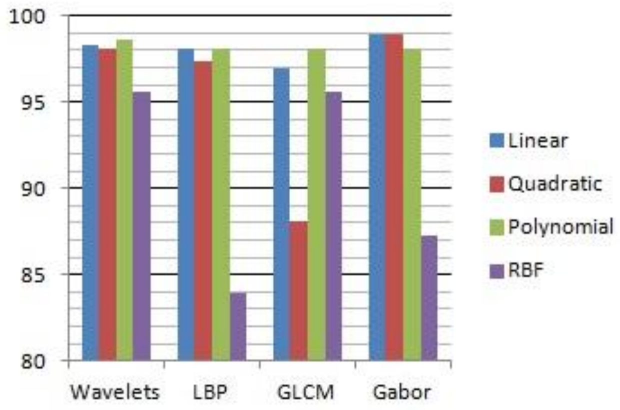


**Fig. 5. Classification accuracy for the combination of color moments and other textures with 4 kernel functions for 40% training using SVM with One-Against-One approach.**

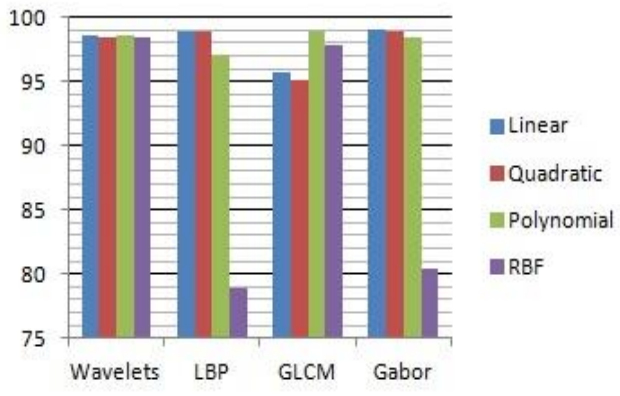


**Fig. 6. Classification accuracy for the combination of color moments and other textures with 4 kernel functions for 40% training SVM with One-Against-All approach.**

**Table 2. Classification accuracy of Color Histogram and texture features using SVM One-Against-One approach with 4 kernel functions for 40% training.**

| | Linear | Quadratic | Polynomial | RBF |
|---|---|---|---|---|
| **Wavelets** | 98.33 | 98.13 | 98.61 | 95.56 |
| **LBP** | 98.19 | 98.08 | 97.15 | 85.28 |
| **GLCM** | 97.51 | 98.03 | 98.01 | 96.11 |
| **Gabor** | 98.67 | 98.67 | 97.78 | 85.17 |

**Table 3. Classification accuracy of Color Histogram and texture features using SVM One-Against-All approach with 4 kernel functions for 40% training.**

| | Linear | Quadratic | Polynomial | RBF |
|---|---|---|---|---|
| **Wavelets** | 96.66 | 98.31 | 98.61 | 90.27 |
| **LBP** | 98.61 | 98.05 | 96.29 | 78.89 |
| **GLCM** | 96.67 | 93.28 | 98.64 | 91.89 |
| **Gabor** | 99.05 | 98.56 | 97.81 | 81.88 |

**Table 4. Classification accuracy of Color Moments and texture features using SVM One-Against-One approach with 4 kernel functions for 40% training.**

| | Linear | Quadratic | Polynomial | RBF |
|---|---|---|---|---|
| **Wavelets** | 98.33 | 98.13 | 98.61 | 95.56 |
| **LBP** | 98.15 | 97.41 | 98.06 | 83.89 |
| **GLCM** | 96.94 | 88.06 | 98.06 | 95.56 |
| **Gabor** | 98.89 | 98.89 | 98.06 | 87.22 |

**Table 5. Classification accuracy of Color Moments and texture features using SVM One-Against-All approach with 4 kernel functions for 40% training.**

| | Linear | Quadratic | Polynomial | RBF |
|---|---|---|---|---|
| **Wavelets** | 98.66 | 98.44 | 98.66 | 98.43 |
| **LBP** | 98.88 | 98.88 | 97.03 | 78.89 |
| **GLCM** | 95.78 | 95.11 | 98.88 | 97.83 |
| **Gabor** | 99.02 | 98.9 | 98.42 | 80.33 |

## IV. CONCLUSION

The above work aims at classification of coconuts using the combination of color and texture features. The classification is carried out using SVM with two different approaches One-Against-One and One-Against-All. To analyze the impact on classification accuracy we used four different kernel functions. The combination of color moments and Gabor texture with One-Against-All SVM approach having linear kernel function shows a good accuracy of 99.02% with 40% training. The other kernel functions for the same combination also gave comparatively good result and the difference in classification accuracy is insignificant. The above experimentation is carried out in a theoretical setup, same need to be experimented for a practical real time scenario, which helps in testing the effectiveness of this model.


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## REFERENCES


1. P. Balamurugan and R. Rajesh, "*Neural Network Based System for the* Classification of Leaf Rot Disease in Cocos Nucifera Tree Leaves," European Journal of Scientific Research, vol. 88, no 1, 2012, pp.137-145
2. R. Chakravarti and X. Meng, "A Study of Color Histogram Based Image Retrieval," Proc. Sixth International Conference on Information Technology: New Generations, 2009, pp.1323-1328.
3. M.J. Swain, D.H. Bellard, "*Color Indexing*," International Journal of Computer Vision, vol.7, no.1, 1991, pp.11-32.
4. M. Stricker and M Swain, "*The Capacity and the Sensitivity of Color Histogram Indexing*," Technical Report, 94-05, 1994.
5. M.K. Mandal, T. Aboulnasr, and S. Panchanathan, "*Image indexing using moments and wavelets*," IEEE Transaction on Consumer Electronics, vol. 42, no.3, 1996, pp.557-565
6. M. Stricker and M. Orengo, "*Similarity of color images*," in Storage and Retrieval for Image and Video Databases III, vol. 2420 of Proc. of SPIE, February 1995, pp. 381–392.
7. S. Ghosal and R. Mehrotra, "*A Moment-Based Unified Approach to Image Feature detection*," IEEE Transactions on Image Processing, vol. 6, no.6, 1997, pp.781-793.
8. Vailaya, M. Figueiredo and A. Jain. "*Content-based hierarchical classification of vacation images*," Proc. IEEE International Conference on Multimedia Computing and Systems, 2002, pp.1-15.
9. R. C. Gonzalez and R. E. Woods, "*Digital Image Processing*," 3rd ed. Pearson Education, 2009, pp. 523-525.
10. B. S. Manjunath and W. Y. Ma, "*Texture Features for Browsing and Retrieval of Image Data*," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, no. 8, 1996, pp. 837-842.
11. T. Ojala, M. Pietikainen and T. Maenpaa, "*Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns*," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, 2002, pp. 971-987.
12. R. M. Haralick, K. Shanmugam and I. Dinstein, "*Textural Features for image classification*," IEEE Transaction on System, man and Cybermatics, vol. 3, no. 6. , 1973, pp. 610- 621.
13. B. Yekkehkhany, A. Safari, S. Homayouni, and M. Hasanlou, "*A Comparison Study of Different Kernel Functions for SVM-based Classification of Multi-temporal Polarimetry SAR Data*," Proc. of 1st ISPRS International Conference on Geospatial Information Research, 2014, pp.281-285.
14. Y. Liu and Y. F. Zheng, "*One-Against-All Multi-Class SVM Classification Using Reliability Measures*," Proc. of International Joint Conference on Neural Networks, Montreal, Canada, 2005, pp.849-854.
15. J. Weston and C. Watkins, "*Support Vector Machines for Multi-Class Pattern Recognition*," Proc. of European Symposium on Artificial Neural Networks Bruges (Belgium), 1999, pp. 219-224.
16. J. Milgram, M. Cheriet, and R. Sabourin, "*One Against One or One Against All: Which One is Better for Handwriting Recognition with SVMs?*," Proc. of Tenth International Workshop on Frontiers in Handwriting Recognition, 2006. https://hal.inria.fr/inria-00103955.
17. M. A. Nanda, K. Seminar, D. Nandika and A. Maddu, "*A Comparison Study of Kernel Functions in the Support Vector Machine and Its Application for Termite Detection*," Information, vol.9, no. 5, 2018, pp.1-14,
18. C. W. Hsu and C. J. Lin, "*A Comparison of Methods for Multiclass Support Vector Machines*," IEEE Transactions on Neural Networks, vol. 13, no. 2, 2002, pp.415-425.
19. G. M. Foody and A. Mathur, "*A Relative Evaluation of Multiclass Image Classification by Support Vector Machines*," IEEE Transactions on Geoscience and Remote Sensing, vol. 42, no. 6, 2004, pp.1335-1343.
20. C. J.C. Burges, "*A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery*," vol.2, 1998, pp. 121–167.
21. C.W. Hsu, C. C. Chang, and C. J. Lin, "*A Practical Guide to Support Vector Classification*," http://www.csie.ntu.edu.tw/~cjlin/, 2010.
22. Z. Wang and X. Xue, "*Multi-Class Support Vector Machine*," Chapter 2, Book of Support Vector Machines Applications, Springer International Publishing Switzerland, 2014, pp.27-48.
23. C. Cortes and V. Vapnik, "*Support-Vector Networks*," Machine Learning, vol.20, 1995, pp. 273-297.
24. V. Jakkula, "*Tutorial on support vector machine (svm),*" School of EECS, Washington State University, 2006.


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