IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

CLASSIFICATION OF BETEL LEAF BASED ON MATURITY LEVEL USING COLOR AND TEXTURE FEATURES

Deepa G [1], Dhanesha R[2], Maithra A. H[3], Pratyusha S[4]

[1,2,3,4]DOS in Computer Science, Davangere University, Davangere, Karnataka, India

Abstract: Indian Grading of the betel leaf for its maturity muffled to be very crucial in commercial forms that basically crop huge value of betel leaf and individual or domain experts are usually involved in performing the grading of betel leaf based on its maturity parameter. In the recent year automatic vision-based technology has become more powerful and more efficient to many areas including agriculture field and food industry. The most common property to measure quality of the any leaf is its appearance which includes color, shape, size and surface conditions. Our main aim is to establish an automated maturity estimated for betel leaf using computer machine to replace the involvement of an individual. The analysis of color is especially an important consideration when determining the efficiency of leaf. This proposal promotes a system that could identify that leaf maturity in the connection to the color and texture of the betel leaf. The proposed work identifies the premature, mature and over mature betel leaf. Segmentation is performed by using Threshold method. Classification is done using the Random Forest classifier. The proposed work classifies the betel leaf images with an accuracy of 86.3%.

Keywords: Betel leaf, entropy, energy, maturity, immature, classifier, Random forest.

1. Introduction

Betel leaf (Piper betel L.) is an important crop in many countries, including India, Indonesia, and China. It is used for chewing, in traditional medicine, and in religious ceremonies. The quality of betel leaf is determined by its maturity, which is affected by factors such as the variety of betel vine, the climate, and the cultivation practices. Manually assessing the maturity of betel leaf is a time-consuming and labor-intensive process. It is also prone to human error. Image processing can be used to automate the process of betel leaf maturity detection. This can help to improve the efficiency and accuracy of the process, and it can also help to reduce the cost of production. Image processing can be used to automate the detection of betel leaf maturity. This can be done by extracting features from the leaves' images, such as their color, texture, and shape, and then using these features to classify the leaves as mature or immature. It can be difficult to determine the maturity of betel leaves by visual inspection alone. This is because the color and texture of the leaves can vary depending on the growing conditions, the variety of betel leaf, and the age of the plant[1]. For example, betel leaves that are grown in a shady environment may have a lighter green color than betel leaves that are grown in a sunny environment. Additionally, the maturity of betel leaves can change rapidly, making it difficult to track their progress.

India is well known for agricultural country wherein about 70% of the population depends on agriculture. Farmers have wide range of multiplicity to select suitable crops for their farm. However, the cultivation of these crops for optimum yield and quality produce is mostly technical which can be improved by the help of technological support. The management of perennial crops requires closer controlling especially for the management of maturity that may affect production significantly and afterword the post-harvest life of crops.

The image processing is best technique used in agricultural applications for following purposes. First part is estimate the life age for better maturity. We can decide the production stage of our crop. Second part predicts plant maturity from image of plants. The existing method for plant maturity detection is simply naked eye observation by experts through which identification and detection of plant maturity is taken in account. This process is tedious, time consuming. So there is need for designing a system that automatically recognizes, classifies and quantitatively detects plant maturity. In case of plant maturity the maturity is known as any impairment of normal physiological function of plants which produce characteristic. Mostly maturity is seen on the leaves on plants or stems of the plant. Hence to develop a computer vision system to detect, recognize and classify maturity affected leaves comes in the era of current technology so Automatic detection of become the most important research topic as it may prove gain in monitoring large fields of crops and thus automatically detect the maturity of the plant leaves. The system provides an approach that facilitate Capture image, process it and get result through image processing.

Image processing is a technique that can be used to extract information from images. This information can then be used to classify the images or to perform other tasks. Image processing can be used to detect the maturity of betel leaves by extracting features from the leaves' images, such as their color, texture, and shape. These features can then be used to train a machine learning algorithm to classify the images as mature or immature. There are several benefits to using image processing to detect betel leaf maturity[2]. First, it is a more objective and accurate way to determine the maturity of the leaves than visual inspection. Second, it is faster and more efficient than manual inspection.

Third, it can be used to automate the process of harvesting betel leaves, which can save farmers time and money. Image processing is a promising technique for automating the detection of betel leaf maturity. This can be a valuable tool for farmers and growers, as it can help them to harvest the leaves at the optimal time. The accuracy of the image processing system can be improved by using a better quality camera, by taking the images in a controlled environment, and by using a more sophisticated machine learning algorithm.

Betel leaf is divided into immature, matured and over mature based on the percentage on the ripeness. It is important to harvest betel leaves at the optimal stage of maturity to ensure that they have the best flavor and aroma. Immature leaves will be tough and bitter, while over-mature leaves will be soft and have a bland taste. Betel leaf cultivation is an important agricultural activity in India[3]. It is grown as a cash crop in the southern parts of the country, mostly in the states of Andhra Pradesh, Telangana, Karnataka, Kerala, and Tamil Nadu. Betel leaf is also cultivated in Bihar, Assam, Madhya Pradesh, Orissa, Maharashtra, Tripura, Uttar Pradesh, and West Bengal. The ideal climate for betel leaf cultivation is warm and humid, with an average temperature of 25-30 degrees Celsius and a rainfall of 150-200 cm. The soil should be loamy and well- drained. The betel leaf vine is propagated by stem cuttings. The cuttings are planted in the nursery bed and allowed to grow for about 4-6 months. Once the plants are well-established, they are transplanted to the main field.

The betel leaf vine is a climbing plant and needs to be supported by a trellis or a shade net. The plants need to be watered regularly, especially during the summer months. They also need to be fertilized every 2-3 months. The betel leaves are harvested 4-6 months after transplanting. The leaves are plucked by hand and sorted according to their size and quality. The leaves are then packed and transported to the market. India is a major producer of betel leaves. In 2020-21, the country produced about 1.2 million tons of betel leaves. Andhra Pradesh is the leading producer of betel leaves, followed by Tamil Nadu, Kerala, and Karnataka. Betel leaves are used for chewing and are also used in making traditional Indian sweets and snacks. They are also used in traditional medicine. The cultivation of betel leaf is a labor- intensive activity. However, it is a profitable crop and can fetch good returns to the farmers.

A. Related Work

Computer vision and image processing are rapidly becoming more common in precision agriculture. For fruit ripening classification, a variety of approaches based on shape, size, colors, and texture have been devised. Different ways for segmenting fruits to retrieve the features needed for the classification process were also available. Wan, Peng, et al.[4], proposed a method for detecting the maturity levels (green, orange, and red) of fresh market tomatoes (Roma and Pear varieties) by combining the feature color value with the backpropagation neural network (BPNN) classification technique.

Surya Prabha, D., et.al. [5], study attempted to use image processing technique to detect the maturity stage of fresh banana fruit by its color and size value of their images precisely. The mean color intensity from histogram; area, perimeter, major axis length and minor axis length from the size values, were extracted from the calibration images. The mean color intensity algorithm showed 99.1 % accuracy in classifying the banana fruit maturity. The area algorithm classified the under-mature fruit at 85 % accuracy.

Van Huy Pham and Byung Ryong Lee [6], Proposed a method for detecting deficiency in orange fruits was presented. Defects in orange fruits were detected using a segmentation technique. Graph-based and k-means clustering approaches were employed to classify defects in orange fruits.

X.E. Pantazi, et.al [7] proposed an automated approach for detecting leaf disease in numerous crop species by evaluating image features and deploying a classifier. The feature extraction was done with Local Binary Pattern (LBP), and the illness leaf classification was conducted with a support vector machine (SVM) classifier. Yanan Li, Zhiguo Cao, et.al [8], presented a technique for detecting in-field cotton using image segmentation. Unsupervised region creation and supervised semantic labeling prediction were utilized in conjunction with region-based segmentation. Each region was segmented using histogram-based color and texture features.

NST Saia, Ravindra Patil, et.al [9], developed a content-based image retrieval system which used two distinct feature vector methods. For gray scale, RGB, and YCbCr color images, the SVD (singular value decomposition) feature of increasingly truncated DCT (Discrete cosine transform) images and the DWT (Discrete wavelet transform) decomposed image were computed. The relevant images from the dataset were extracted based on color feature. Yaqoob Majeed, Jing Zhang, et.al [10], proposed a segmentation method to segment Apple trunk and branch. The images were stored in cloud from Kinect V2 sensor and using deep learning-based semantic method the images are segmented. To remove the background trees Depth and RGB features are extracted from cloud data.

By using the fundamental K nearest neighbour (KNN) model, Daneshwari Ashok Noola et.al. [11] concentrated on designing and developing the enhanced-K nearest neighbour (EKNN) model. EKNN is used to differentiate between illness classes. High-quality fine and coarse features are produced to gather discriminative, boundary, pattern, and structurally linked information, which is then utilized in the classification process. Gradient-based characteristics of excellent quality are provided by the classification procedure. Uoc Quang Ngo et.al. [12], devised a technique for precisely calculating the leaf area of cucumber plants using digital image processing. The suggested ways extract the cucumber plant's skeleton from RGB images and correctly estimate the leaf area of cucumber plants.

Megha.P.Arakeria, Lakshmana [13], To assess tomato quality, a computer vision method with 2 phases was developed. The hardware was created in the initial phase to collect tomato images and transport tomato fruit to suitable containers. The software was developed in the second phase to detect defects and ripeness in tomato fruit using image processing techniques. The RGB color model was used to determine ripeness. Yang Yu and Sergio A. Velastin, et.al [14], proposed a quick and efficient approach for achieving automated apple grading . For each apple sample, four images were taken (top, bottom and two sides). To differentiate the apple deformities, stem, and calyx, the grey value of each apple was acquired. K-means clustering was utilized to find the defective zone in an apple. Santi Kumari Behera, et.al [15], applied KNN, SVM and Naive Bayes classifier to classify the papaya fruits based on maturity status. Features such as LBP, Histogram of Oriented Gradients (HOG) and Gray Level Co-occurrence Matrix (GLCM) were extracted from papaya fruit image to fed as input to classifier.

Suresha M, et.al [16], presented a method to classify the diseased arecanut using texture features. The LBP , Haar Wavelets, GLCM and Gabor features of texture were used to determine the diseased arecanut. The HSI(Hue Saturation Intensity) and YCbCr color models were used. The LBP, Haar Wavelets, GLCM and Gabor methods were applied on HSI and YCbCr color model to extract the texture features. The KNN(K-nearest neighbor) classifier was used to classify the diseased and un-diseased arecanut.

Ajit Danti, et.al [17], presented a method for separating raw arecanuts into two categories. Red and green colors were used to determine upper and lower limits for the classification of raw arecanuts. Dhanesha R., et.al [18], introduced a brand-new method for segmenting arecanut bunches using the active contour method. The segmentation methodology was evaluated using the segmentation performance techniques VOE and DSC. Umesha D.K., et.al [19], proposed a study of different color models to segment the arecanut bunches. In order to separate the arecanut bunch from an input image, the HSV, YCbCr, YUV, YCgCr and YPbPr color models are applied to arecanut bunch images with manual threshold. Color models HSV and YCgCr were efficient in segmenting arecanut bunches from other color models used in the study.

According to the literature survey it is observed that the image processing and machine learning plays vital role in the agriculture field to classify the maturity level of vegetables and fruits. So, in this proposed work the image processing techniques are applied to classify the Betel leaf based on maturity level.

B. Feature Extraction for classification

A wide variety of classification processes employ color and texture feature analyses. The maturity levels of Betel leaves were classified using color and texture features. To classify the matured and un-matured Betel leaf the three color features (i.e., the Average intensity on the R, G, and B bands: RAvg, GAvg, and BAvg) were calculated by applying the Equations.

RAvg = sum of (red pixels) / the entire amount of pixels occupied by Betel leaf Image (1)

GAvg = sum of (green pixels) / the entire amount of pixels occupied by Betel leaf Image (2)

BAvg = sum of (blue pixels) / the entire amount of pixels occupied by Betel leaf Image (3)

Texture Features : To classify the Betel leaf along with color features entropy and energy features of texture were used.

C. Classifier

Randomizable Filtered classifier:

Random Forest developed by the Leo Breiman is a group of un-pruned classification or regression tress made from the random selection of the sample of the training data. Random features are selected in the induction process. Prediction in made by aggregation (majority vote for classification or average for regression) the prediction of the ensemble. By sampling N randomly, if the number of cases in the training set is N but with replacement, from the original data. This sample will be used as the training set for growing the tree. For M number of input variables, The variable m is selected such that m<M is specific at each other node, m variables are selected st random out of the M and the best split on these m is used for splitting at random out the M and the best split on these used for splitting the node .during the forest growing, the value of m is held constant. Each tree is growing to the largest possible extend. No pruning is used. Random Forest generally exhibits a significant performance improvement as compared to single tree classifier. The generation error rate that it yields compared favourably to Adaboost, however it is more robust to noise.

D. Classification Performance metrics

The confusion matrix is used to evaluate classification performance based on elements from the matrix. To compare class labels, the terms TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) are employed. The precision and accuracy of the classifier were estimated based on the values acquired for the confusion matrix in the proposed study to evaluate its performance.

- True Positive: These are cases in which predicted as matured (Yes), and they were actual Matured.

$$\text{TP Rate} = \text{TP} / \text{Actual Yes} \quad (4)$$

- True Negative Rate: These are cases in which predicted as un-matured (No), and they were actually un-matured.

$$\text{TN Rate} = \text{TN} / \text{Actual No} \quad (5)$$

- False positive Rate: Predicted matured, but they actually un-matured. (Also known as a "Type I error”).

$$\text{FP Rate} = \text{FP} / \text{Actual No} \quad (6)$$

- False positive Rate: Predicted un-matured, but they actually matured. (Also known as a "Type II error.").

$$\text{FN Rate} = \text{FN} / \text{Actual Yes} \quad (7)$$

- Precision Rate: When it predicts matured, how often is it correct?

$$\text{Precision Rate} = \text{TP}/ \text{Predicted Yes} \quad (8)$$

- Accuracy: The most typical indicator to assess how well the categorization process is working. The ratio of properly identified samples to the total number of samples is used to determine accuracy.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (9)$$

2. Methodology

This section describes the Database used for experimentation. The segmentation techniques to segment Betel leaf using manual thresholding were discussed. And also the tool and the classifier used to classify the Betel leaf based on maturity level were mentioned.

A. Database

The Database contains 73 colored images which are captured with help of a smart phone fitted on selfie stick. These images were taken at different time of the day.

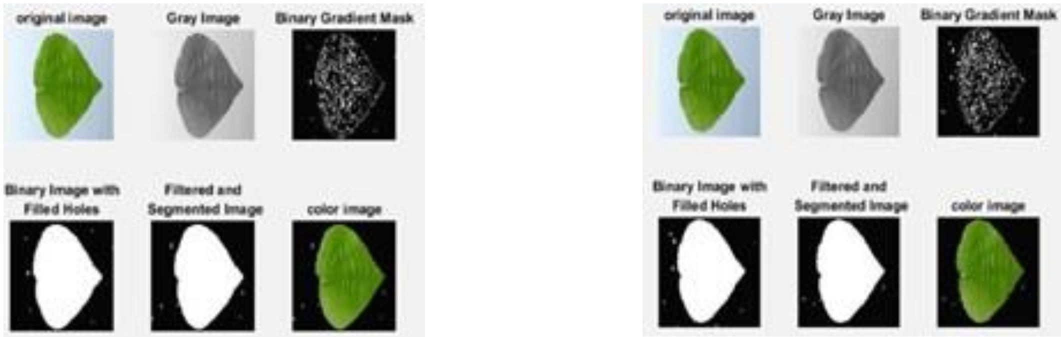
B. Segmentation and Classification: Segmentation divides an image into its constituent regions or objects. The level of detail to which the subdivision carried depends on the problem using being solved. i.e., segmentation should stop when the objects or regions of interest in an application have been detected. The input image is segmented using manual thresholding. In this proposed work the sobel mask with edge detection algorithm is used to segment the image. The output of edge segmentation is applied with morphological operations such as hole filling, than the median filter is applied to filter the image to get the region of interest. The image is transformed back to its RGB format. RGB components were recovered independently from the RGB segmented image to compute the average of each component. To extract entropy and energy texture features, an RGB segmented image is transformed to a gray scale image and using GLCM function available in Matlab these features were extracted. The computed feature values were saved in a.csv file.

The .csv file is used as an input by the Weka 3.8.4 utility. The black barriers are classified depending on their maturation stage using a RandomizableFiltered classifier. The values of the confusion matrix were used to calculate precision and accuracy metrics to evaluate the performance of classification.

3. Experiment and Results

A. Experiment

In order to categorize the maturity level of 73 images of immature and mature Betel leaf, experiments were conducted. To classify them, certain features were required.



(a) (b)

Fig 1: Segmentation Process of a) Immature Betel Leaf b) Matured Betel Leaf

The Figure 1., shows the output of segmentation process. After segmentation color and texture features were taken from segmented images to execute the classification procedure. To extract the RGB components of an image, a segmented image is transformed to an RGB image. Color and texture features were extracted using GLCM method of MATLAB 14b.

The retrieved feature values were entered into the Weka 3.8.4 tool (.csv file). The experiment was carried out using aRandomizableFiltered classifier. The parameters set in RandomizableFiltered classifier are as follows:

- **Cross-Validation Fold:** is a method of the Evaluation class that is employed to carry out cross-validation using a single dataset and an untrained classifier. Cross-Validation Fold is given a value of 10 (default value).
- **BagSizePercent:** Size of each bag, as a percentage of the training set size. Value assigned is 100.
- **BatchSize:** The preferred number of instances to process if batch prediction is being performed. Value assigned is 100.
- **NumIterations:** The number of trees in the random forest. Value assigned is 100.

Other parameters were set to default value assigned by Weka 3.8.4. The findings were discussed in the section Results and Discussion.

4. Results and Discussions.

Betel leaves are first segmented to extract required features before being classified according to maturity level. With dataset images provided with the proposed method, the segmentation results are compared to manually graded ground truth (GT). The value of the retrieved features is saved in .csv file with six columns labelled RAvg, GAvg, BAvg, Correlation, Entropy, and Class. There are two values in the Class column. Yes or No. Yes denotes matured Betel leaf, whereas No denotes immature Betel leaf.

Table 1: Performance of classifier evaluation using Confusion Matrix

N=1017	Predicted NO	Predicted YES	Correctly Classified	Precision	Accuracy(%)
Actual YES(30)	FN=9	TP=21	30	0.8630	**86.3%**
Actual No(17)	TN=42	FP=01	15		
Total(73)	51	22	73		

The performance of classification is assessed using precision and accuracy metrics based on confusion matrix values, as shown in table 1. Table 1, shows that 73 samples out of 63 dataset samples were correctly classified, resulting in a 8**6.3%** of accuracy.

5. Conclusion

This study has proposed a method for betel leaf maturity detection using image processing. The method was able to classify betel leaf images into different maturity stages with high accuracy. The results of this study suggest that image processing can be used to automate the process of betel leaf maturity detection. This can help to improve the efficiency and accuracy of the process, and it can also help to reduce the cost of production. In this project, we developed a method for automatically detecting the maturity of betel leaves using image processing techniques. We collected a dataset of images of betel leaves at different stages of maturity, and used this dataset to train a MATLAB. It was able to achieve an accuracy of 86.3% in classifying the maturity of betel leaves.

References

1. Kumar, V., & Suresh, A. (2019). Betel leaf maturity detection using texture features. International Journal of Innovative Technology and Exploring Engineering, 8(4), 3275-3279.
2. P. Guha Betel Leaf: The Neglected Green Gold of India, Agricultural and Food Engineering Department, Indian Institute of Technology Kharagpur, West Bengal, India J. Hum. Ecol., 19(2): 87-93 (2006).
3. Suresh, A., & Kumar, A. (2017). Betel leaf maturity detection using digital image processing. International Journal of Computer Applications, 166(1), 1-6.
4. Wan, Peng, et al. "A methodology for fresh tomato maturity detection using computer vision." Computers and electronics in agriculture 146 (2018): 43-50.
5. Surya Prabha, D., and J. Satheesh Kumar. "Assessment of banana fruit maturity by image processing technique." Journal of food science and technology 52 (2015): 1316-1327.
6. Van Huy Pham and Byung Ryong Lee. An image segmentation approach for fruit defect detection using k-means clustering and graph-based algorithm. Computer Science, 2:25–33, 2015.
7. A.A. Tamouridou X.E. Pantazi, D. Moshou. Automated leaf disease detection in different crop speciesthrough image features analysis and one class classifiers. Elsevier Journal of Computers and Electronicsin Agriculture, 156:96–104, 2019.

8. Yanan Li, Zhiguo Cao et.al. In field cotton detection via region-based semantic image segmentation. Elsevier Journal of Computers and Electronics in Agriculture, 127:475–486, 2016.
9. NST Saia, Ravindra Patil et.al. Truncated dct and decomposed dwt svd features for image retrieval. In Proc. Elsevier Conf. 7th International Conference on Communication, Computing and Virtualization, volume 79, page 579 – 588, 2016.
10. Yaqoob Majeed, Jing Zhang et.al. Apple tree trunk and branch segmentation for automatic trellis training using convolutional neural network based semantic segmentation. In Proc. Elsevier Conf. IFAC(International Federation of Automatic Control) PapersOnLine, pages 51–17, 2018.
11. Daneshwari Ashok Noola et.al., "Corn leaf image classification based on machine learning techniques for accurate leaf disease detection", Indonesian Journal of Electrical Engineering and Computer Science, Vol. 12, No. 3, June 2022, pp. 2509-2516, ISSN: 2088-8708, DOI: http://doi.org/10.11591/ijece.v12i3.
12. Uoc Quang Ngo et.al., "Digital image processing methods for estimating leaf area of cucumber plants", Indonesian Journal of Electrical Engineering and Computer Science, Vol 25, No. 1, January 2022, pp. 317-328, ISSN: 2502-4752, DOI: http://doi.org/10.11591/ijeecs.v25.i1.
13. Lakshmana Megha.P.Arakeria. Computer vision based fruit grading system for quality evaluation of tomato in agriculture industry. In Proc. Elsevier Conf. 7th International Conference on Communication, Computing and Virtualization, volume 79, page 426 – 433, 2016.
14. Yang Yu and et.al Sergio A. Velastin. Automatic grading of apples based on multi-features and weighted k-means clustering algorithm. Information Processing in Agriculture, 2019.
15. Santi Kumari Behera et.al. Maturity status classification of papaya fruits based on machine learning and transfer learning approach. Information Processing in Agriculture, 2020.
16. S. K Narasimhamurthy Suresha M, Ajit Danti. Classification of diseased arecanut based on texture features. Computer Applications (0975 – 8887) Recent Advances in Information Technology, 2014.
17. Suresha M Ajit Danti. Segmentation and classification of raw arecanuts based on threesigma control limits. Elsevier Journal of C3IT-2012, 4:215 – 219, 2012.
18. Shrinivasa Naika C. L. Dhanesha R. A novel approach to segment an arecanut bunches using active contour method. In Proc. Springer,2nd International conference on Integrated Intelligent Computing, Communication And Security, pages 677–682, 2019.
19. R. Dhanesha, D. K. Umesha, C. L. Shrinivasa Naika and G. N. Girish, "Segmentation of Arecanut Bunches: a Comparative Study of Different Color Models," 2021 IEEE Mysore Sub Section International Conference (MysuruCon), 2021, pp. 752-758, doi: 10.1109/MysuruCon52639.2021.9641680.