International Journal of Research in Advent Technology, Vol.7, No.3, March 2019
E-ISSN: 2321-9637
Available online at www.ijrat.org

Classification of Arecanut using Neural Networks with Feed-forward Techniques

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Abstract- This paper presents a classification of Arecanut using Neural Networks. Segmentation of arecanut performed using a popular method, structural matrix decomposition (SMD)method. A two well-known features are used to extract the GLCM and Geometrical features. The Feed-Forward neural network (NN) algorithm is used four verities of arecanuts such as, Api, Sagatu, Nice idi, Gotu classification. Experiment conducted on 240 images. Fusion of GLCM, Hue- GLCM and Shape features gives best result compare to the other features and it gives 88.30 % accuracy.

Keywords - GLCM, Shape Features, Feed-forward NN.

1. INTRODUCTION

Arecanut palm is one of the significant commercial crops of India. Arecanut is the main plantation crop of costal and southern districts of the country under certain irrigation facility. India is the foremost producer and consumer of arecanut in the world. Arecanut is used in traditional ayurvedic medicines, chewing arecanut and betel leaf is a good remedy against bad breath. Newly it has been reported that arecanut powder extract is capable of reducing silver ions to silver nano particles, which may be antimicrobial agents. It forms one of the ingredients of betel quid commonly in India, It has an integral part in several religious and social ceremonies. Alternative uses of arecanut found that tannins, a by-product from the processing of young nuts find use in dyeing clothes, tanning leather, as a food colour, as mordant in producing variety of shades with metallic salts . It contain 8-12% of fat, which can be extracted and used for chocolate purposes. The refined fat is harder than cocoa butter and can be used for mixing. The arecanut leaf sheath could be used for preparation of dispose of cups, plates, plyboards, tea chest, packing cases and suitcases and these are commercially exploited to some extent.

Areca farming is a type of business which farmers do alongside with their crop farming. Indian farmers face huge pressure when it comes to the separation of processed arecanuts. When it comes to paying wages to the labourers for their manual effort of segregating areca nuts based on their quality, the farmers suffer a loss of money and time which are trying to prevent by using computer vision.

2. RELATED WORK

In [1], proposed Evaluation of shape and color features for classification of four paddy varieties they have been determined the shape, color and shape-n-color features were extracted from images of individual grains and the same were assessed for classification of grains. The accuracy shown is 88.00%, 74.02%, and 89.00% with shape, color and shape-n-color features respectively. The most satisfactory results were delivered by the shape-n-color feature set. Only, Color feature set gave lower accuracy than all other sets because the difference between the features of different varieties is negligible. It can be concluded that invariant moments, standard moments and central moments of shape along with color mean, standard deviation and variation have a significant role in discriminating the paddy varieties. In [2], proposed work, a separation system, based on combination of acoustic detection and artificial neural networks, was designed for classifying four Iranian's export pistachio nut varieties. This method has high accuracy and can be adapted to recognize other pistachio varieties or in other applications such as separation of open and closed shell pistachios. MLP network was employed for pistachio nut classification. Features of pistachio nut varieties were extracted from analysis of sound signals in both time and frequency domains by means of Fast Fourier Transform (FFT), power spectral density (PSD) and principal component analysis (PCA) methods. For finding the best combination for minimum number of principle components with highest accuracy and for creating the network input vector, 37 different combinations of PCA components were fed to network as input vector. Altogether 40 features were selected for classifications: 24 amplitude features, 10 PSD features and 6 phase features. A combination of these 40 features resulted in a minimum feature number with highest classification accuracy in network training time. Selected optimal neural network for classification exhibited a 40 – 12 - 4 structure, with 12 neurons in its hidden layer. Total weight average in system accuracy was 97.51%. In [3], a combined color, texture and edge features based approach for Identification and

Classification of Indian medicinal plants has been proposed. Classified medicinal plants as herbs, shrubs and tree based on color and texture feature used SVM (Support Vector Machine) and Neural Network Classifier. Database containing 900 images of medicinal plants is used for experiments. Claim classification accuracy result for color and texture feature is 74% and 80% respectively and combination is of 90%. In [4] Authors proposed a classification for arecanut based on texture using decision tree classifier. In their work, texture based features particularly mean around features and gray level co-occurrence futures (GLCM) are extracted and efficiently represented. Decision trees classifier procedure has used to classify six verities of arecanut and claim 99.05 % of success rate of classification. In [5] Authors proposed a method for classifying almond images into three classes (object, shadow and background) based on combined image processing and ANN was proposed and evaluated. The results of the different segmentation methods showed that the proposed method outperformed Otsu, dynamic thresholding and watershed segmentation methods. Also, this method due to the low processing time can be used in real time applications. The proposed method for separating almonds in all classes in the images had the highest precision without applying any noise reduction technique. Yet, the correct classification rate was further improved after applying noise reduction technique. In the Otsu, dynamic thresholding and watershed methods the best performance was obtained for wrinkled almonds and the worst performance was obtained for almond shells and broken almonds. However, in they method the best performance was related to broken almonds and the worst performance was due to almond shells. The proposed methodology showed good potential to classify almond images into object, background, and shadow classes. By eliminating the Effect of shadow around the objects the performance of segmentation process is improved.

3. PROPOSED METHODOLOGY

In the rest of this paper, described introduction and application of arecants in section 1. Related work briefly in Section 2, proposed methodology discussed in section 3. Experimental result illustrated in section 4. Finally, concluded the paper in Section 5 and Fig.1shows the proposed classification of arecanuts.

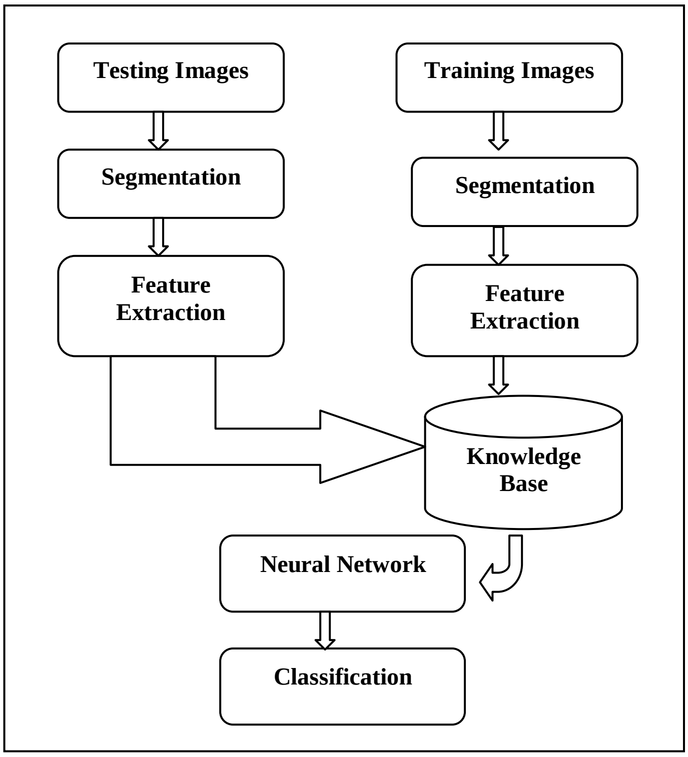

Fig. 1. Flow diagram for proposed methodology.

3.1. *Segmentation*

In this section, describe salient object segmentation technique that uses the Structural matrix decomposition (SMD) model. SMD technique contains two main steps: the first one focuses on low level features, second one incorporates high-level prior knowledge. Fig. 2 shows the framework of SMD-based salient object segmentation. Salient object segmentation techniques SMD consists of four steps: image abstraction, index tree construction, matrix decomposition, and saliency region segmentation.

Step 1: Image Abstraction: In this step, an input image is partitioned into compact and intuitive homogeneous elements. To construct a 53-dimension feature representation, first extract the low-level features, as well as RGB color, steerable pyramids [8]and Gabor filter [9].Then, performing the over-segmenting the image into N number patches using simple linear iterative clustering (SLIC) algorithm .

P = fP1; P2; _ _ _ ; PNg. Each patch P_i is represented by a feature vector f_i, and all these feature vectors form the feature matrix as F =[f1; f2; : : : ; fN] (here D = 53) [10].

Step 2: Tree construction on P, an index tree T is constructed to encode structure information via hierarchical segmentation after computing the affinity of every adjacent patch pair. Then, apply a graph-based image segmentation procedure to merge spatially neighboring patches according to their affinity [11]. The algorithm produces a sequence of coarseness-increasing segmentations. In each

coarseness layer, the segments correspond to the nodes at the corresponding layer in the index tree. Specifically, the granularity is controlled by an affinity threshold T. Finally, we obtain a hierarchical fine-to-coarse segmentation of the input image [10].
Step 3: Matrix Decomposition. In this step consider both the feature matrix F and the index tree T are ready, apply the SMD model, and decompose F into a low-rank component L and a structured-sparse component S. After jointly imposing the structured-sparsity and Laplacian regularization, the input feature matrix F is decomposed into structured components L and S [10].
*Step 4***:** Saliency Assignment. Afterward decompose of F, transfer the results from the feature domain to the spatial domain for saliency estimate based on the structured matrix S, and define a straightforward saliency estimation function of each patch in P [10]. Structural matrix decomposition segmentation and sample of different arecanut types shown in Fig. 2

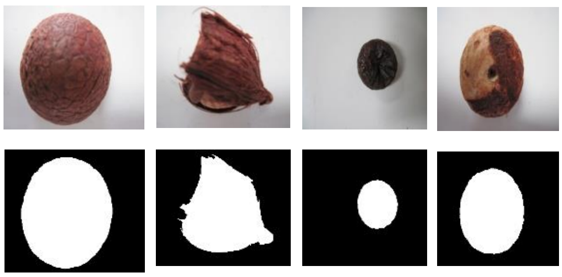

Figure. 2: Segmentation of images using SMD.

3.2. *Feature Extraction*

3.2.1 *GLCM*

One of the most popular methods in feature selection is the Gray Level Co-Occurrence Matrix (GLCM). In [7]GLCM is a statistical technique, extracting the textural feature from images. The texture is used to distinguish the surface of a given object and it is undoubtedly one of the main features used in pattern recognition and image processing. Correlation, contrast, energy and Homogeneity are considered for experiment.

Correlation $$\frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j)\,p(i,j)-\mu_x\mu_y}{\sigma_x\,\sigma_y} \quad (1)$$

Contrast $$\sum_i\sum_j(i,j)^2 p_d\,(i,j) \quad (2)$$

Homogeneity $$\sum_i\sum_j\frac{1}{1+(i+1)^2}\,g_{ij} \quad (3)$$

Energy $$\sum_i\sum_j g_{ij}^2 \quad (4)$$

3.2.2 Shape Features

In this proposed work geometrical features are extracted of different types of arecanut, using connected component reduced the image data by measuring certain properties of each segmented region. Arecanut are different in shape and size so the bellow mentioned geometrical features considered.
*Area***:** The number of pixels in the shape of the segmented area [6]. In the proposed work feature area, this calculates the area of properly segmented region that area will differentiate from types of arecanuts.

$$\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}p(x,y) \quad (5)$$

Minor Axis Length: The minor axis is derived perpendicularly, where the line has maximum length. First the end point of the minor axis has been oriented; length is given by the same equation as the major axis length. So that it is also called as object width [6]. In the proposed work minor axis length of the segmented part is considered, because the arecanut seed images have round or circle shape or oval shape, so we considered Minor axis as a one of attributes.

$$\sqrt{(x_2-x_1)^2-(y_2-y_1)^2} \quad (6)$$

Major Axis Length: The major axis is derived horizontally; points are the two points in an object where the object is more length and where the straight line drawn among these two points is the elongated. Major axis points are calculated by all possible groupings of perimeter pixels where the line is the extensive. The length of the major axis is given by:

$$\sqrt{(x_2-x_1)^2-(y_2-y_1)^2} \quad (7)$$

Perimeter: Perimeter is an essential feature of an object. Contour based features which ignore the interior of a shape, depend on finding the perimeter or boundary points of an object (Costa, L. F et al, 2001) [6]. The perimeter of an object is given by the integral as follows:

$$T = x(t) + y(t)dt \quad (8)$$

3.2.3 Hue-GLCM

GLCM is a statistical technique, extracting the textural feature from images. [7] Here author implement RGB image converted into HSV image and extract only Hue component image. The texture feature obtained from Hue component image using Correlation, contrast, energy and Homogeneity.

Correlation $$\frac{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i,j)\,p(i,j)-\mu_x\mu_y}{\sigma_x\,\sigma_y} \quad (9)$$

Contrast $$\sum_i\sum_j (i,j)^2 p_d\,(i,j) \quad (10)$$

Homogeneity $$\sum_i\sum_j \frac{1}{1+(i+1)^2}\, g_{ij} \quad (11)$$

Energy $$\sum_i\sum_j g_{ij}^2 \quad (12)$$

3.3 Classification

An Artificial Neural Network (ANN) is an information processing pattern that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this pattern is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unity to solve specific problems. ANNs, like people, learn by example. In [11]An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

The processing ability of the network is stored in the inter unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns[12].Author, firstly, create an artificial neural network using MATLAB tools and artificial neural network using Feed-Forward with tan-sigmoid transmission function in the hidden and output layers [13]. Feed-forward neural network are part of artificial networks as the connection between the nodes do not flow in cycle form. It was primary type of artificial neural network designed and simple to understand. In feed-forward neural network information flows in forward action (there is no loop), initial passed input layer through hidden layer, next through the hidden layer, and finally through the output nodes and cross entropy (CE) error are used to calculate performance computed outputs and target outputs in NN. CE is best performance compared to MSE. Plotting the training, validation, and test performance using Cross-Entropy inFig.6.

$$CE = -\sum_{i=0}^{n} ln(o_i) * t_i \quad (13)$$

In this network, use 20 neurons in the hidden layer. The network has 12 inputs and 7 outputs shown Fig.4.NN implement in three major steps. First, to set number of hidden layer and number of neurons. Secondly, it provides pre-process facility; the data of same extra rows are removed if it is available. Finally, classify all input data to groups.

4. EXPERIMENTAL RESULTS AND DISCUSSION

(AjitDanti and Suresh), have conducted field survey to create a dataset of arecanut about thirty agricultural fields and fifteen tender markets of arecanut and found different verities of arecanut. Authors found that there are few local varieties of arecanut are considered for this work. Experimental result conducted on arecanut dataset using classification of arecanuts using feed forward NN algorithm. Here considered for four verities of arecanut such as Api,Nice idi,gotu and sagatu. Table 1 shows sample of 240 images randomly selected for training 144 images, validation 36 images and testing 60 images and four class target value shows in table-2. In experimental result classification accuracy rate find using to well known features. Such as GLCM and Geometrical features. Fig. 3 Architecture and execution of neural network, Fig. 4 Plots histogram error for fusion of three features, Fig. 5 shows best validation performance at epoch 21 for GLCM, Fig. 6 shows confusion matrix for 4-class using fusion three features. Based on table.3 and Fig. 7 shows graphical representation of accuracy rate compared with combination of features. Finally, authors conclude combination of three features given best result.

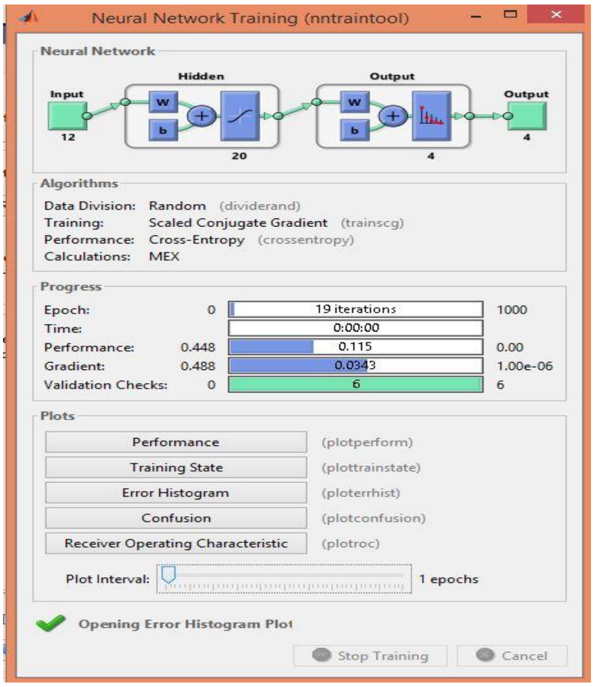

Fig 3: Architecture and execution of neural network.

Table.1: Division of samples for training, validation, and testing.

Stages	Sample in %
Training Samples	60%
Validation Samples	15%
Testing Samples	25%

Table.2: Target value for each sample in NN.

Class-name	Target value
Class-1	0 0 0 1
Class-2	0 0 1 0
Class-3	0 1 0 0
Class-4	1 0 0 0

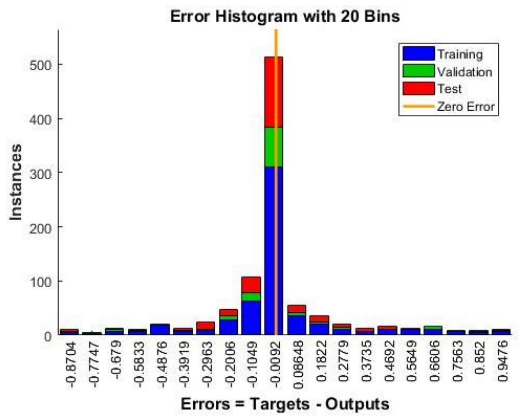

Fig 4: Plots histogram error for fusion of three features.

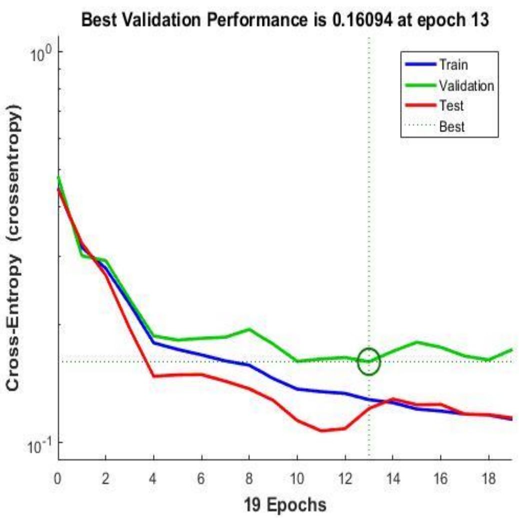

Fig 5: Best validation performance at epoch 19 for fusion of three features.

Table.3: Comparison accuracy rates for features.

No	Features	Accuracy %
1	GLCM	80.00
2	Shape	71.70
3	Hue- GLCM	71.70
4	Shape + Hue-GLCM	73.30
5	GLCM + Hue-GLCM + Shape	**88.30**

Fig 6: Confusion matrix for 4-class for combination of GLCM, Hue-GLCM and Geometrical features.

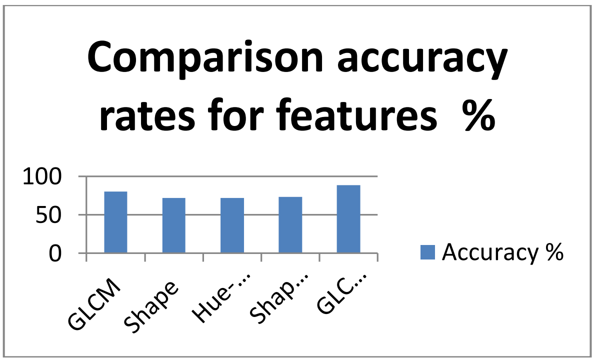

Fig 7. Shows graphical representation of accuracy rate compared with combination of features.

5. CONCLUSION

In present era, neural network (NN) plays important role in pattern recognition and computer vision. This paper demonstrates, classification of arecanut using two features such as texture based GLCM and Geometrical features. Using GLCM feature given 80%, shape feature 71.70 and combination of GLCM and Geometrical given 88.30%. Finally, experimental results conclude that, combination feature perform well against other features.

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