CLASSIFICATION OF ARECANUT USING DIGITAL IMAGE PROCESSING

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Abstract— In agricultural domain research, image processing and machine learning techniques play an important role. One of India's major cash crops is arecanut. A significant challenge in the field of agriculture is the grouping of arecanut. Arecanut categorization using image processing is an emerging field of research that aims to automate the process of grouping arecanut based on its color and shape using digital images. This paper presents a classification of Arecanut using Convolutional Neural Networks.

General Terms

Image Processing, Classification

Keywords

Arecanut classification, Machine learning, Convolutional Neural Networks, Deep learning.

1.INTRODUCTION

Digital Image Processing plays an important role in agriculture domain. It also refers to the manipulation and enhancement of pictorial information with the aim of improving human interpretation. Image processing has become an essential part of numerous applications across various domains, including medicine, entertainment, surveillance, robotics, and more. Agriculture and farming as a backbone of many developing countries to provide food.Arecanut being the major plantation in India. Areca nuts, also known as "betel nuts," indeed hold significant religious, social, and cultural importance in India. IN India it is primarily cultivated in coastal and southern districts of the country, particularly in areas with suitable irrigation facilities. India ranks top in both cultivation area and production of arecanut (47%). The habit of chewing Arecanut is typical of the Indian sub-continent and its neighborhood. India accounts for about 57 percent of world Arecanut production. The quality, variety and types of Arecanut vary from one place to another. Agriculture is labor intensive, time consuming.

Arecanuts can be divided into a number of groups according to the nations and geographical regions in which they are found. Due to its versatility and variety of uses, arecanut is classified into a number of different varieties by various businesses. Maturity, color, glossiness, moisture level, weight, size, shape, texture, etc. Farmers in India are under a great deal of pressure when it comes to separating the processed arecanuts. Farmers experience a loss of money and time when it comes to paying payments to the laborers for their laborious work of manually sorting areca nuts based on their quality, which is something that computer vision is attempting to address. Arecanut classification using digital image processing techniques offers a non-destructive and efficient approach for assessing the quality and grading of arecanut, which is traditionally done manually. By automating this process, farmers and traders can save time, reduce errors, and improve overall productivity. The use of technology in agriculture has indeed evolved significantly, revolutionizing the way farmers approach various processes and decision-making. Initially, technology was introduced to address the challenges and complexities involved in manual calculations and tasks related to agricultural processes. Agricultural automation can take advantage of machine vision capabilities, which can be used in various tasks such as inspection, grading, projected output, automated autonomous machine selection and guidance. We have considered three different types of arecanut like Chaali, Bette and Saraku. In this paper the present work; focus on classifying the areacnuts based on these Preprocessing of the Image, segmentation by Edge detection and classification based on feature extraction.

2. RELATED WORK

To the best of our knowledge classification of arecanut has not been completely using advanced computer vision. There have been some techniques came into existence for classification of different types of arecanut.

"Comparison of a Bayesian classifier with a multilayer feed-forward neural network using the example of plant, soil, or weed discrimination," by J.A. Marchant and C.M. Onyango.Using color and positional information, the authors of this work classify images into plant, weed, and soil components. The Bayes theorem and Bayes rule are used to form the essential tenet of a Bayesian classifier (James, 1985). The Bayes theorem is used in practice to convert probabilities that can be inferred from training data into those needed for classification. Zhang (2000) describes the use of feed-forward neural networks for classification (as well as of many other aspects of classification in general). The limitations imposed by Gaussian assumptions in a Bayesian classifier, however, are frequently implied by Zhang at various points. [1].

Bharadwaj N K and Dr. Dinesh.R, "Possible Approaches to Arecanut Sorting / Grading using Computer Vision: A Brief Review", In this paper different digital image processing techniques are considered further the classification of Arecanut is based on color, shape and texture etc, Arecanut can be classified with the help of color features. In raw Arecanut color plays a prominent role as most of the raw Arecanut classification will be done based on color only. for textural characteristics, The term "image texture" refers to a collection of metrics used in image processing to quantify the texture of a picture as it has been obtained. Using image texture, we can learn how colors or intensities are distributed spatially in an image or in a specific area of an image. [2].

"Areca Nut Disease Detection Using Image Processing Technology", Dhanuja K. C. and Mohan Kumar H. P. The machine vision system used in this study was created to locate and categorize the areca nodes as outstanding, decent, and poor. Levels, Here, the classification process were based on the DL algorithm, BPNN classification, and imaging approaches. Method of classification the imaging methods and the DL algorithm enable accurate segmentation of the faulty regions. In particular, the mean values of the red channel (R), the mean values of the green channel (G), and the mean values of the blue channel (B) were found to be three color characteristics. Six other geometrical characteristics were also measured: the major axis length, axis length, area, perimeter, compactness, and spot areas..In this project they aim to build a fully automated image classification system to identify different diseases in arecanut [3].

S Siddesha, S K Niranjan and V N Manjunath Aradhya,"Color Features and KNN in Classification of Raw Arecanut images", In this paper the authors proposed the model involves three stages: Segmentation, feature extraction and classification. The Segmentation is used to remove the shadow created area while capturing the images. After segmenting the images, color histogram and moment features are extracted. For classification they used KNN classifier with four distance measures which is supervised in nature [4].

"Classification of Diseased Arecanut based on Texture Features", Suresha M, Ajit Danti, and S. K. Narasimhamurthy In the suggested study, textural features from the Local Binary Pattern (LBP), Haar Wavelets, GLCM, and Gabor have been used to classify infected and undiseased arecanuts. The Otsu method is used for arecanut image segmentation. KNN classifier and texture features have both been utilized for classification. This work has been done in two stages for this project. The HSI and YCbCr color models' individual color components were individually subjected to LBP in the first stage and an LBP histogram was created. Texture features from Haar wavelets, GLCM, and Gabor have been employed in the second step. [5].

The classification of arecanuts using neural networks and feed-forward techniques was proposed by Chandrashekhara H, and Suresh M. In this work, the structural matrix decomposition (SMD) approach was used to segment the arecanut. The GLCM and geometrical characteristics are extracted using two well-known features. In order to classify four varieties of arecanuts, including Api, Sagatu, Nice idi, and Gotu, the Feed-Forward Neural Network (NN) technique is utilized. There are 240 photos used in the experiment. The categorization of arecanuts utilizing two features, such as texture-based GLCM and geometric features is demonstrated throughout this work. [6]

3. MATERIALS AND METHODS

3.1. Methodology

The proposed methodology begins with Image acquisition using high-resolution mobile or DSLR cameras to capture Chaali, Bette, and Saraku areca nut images. The Preprocessing stage follows, enhancing image quality by resizing and reducing noise using Gaussian and Laplacian filters. Subsequently, Segmentation separates the areca nuts from the background using the watershed algorithm. After successful segmentation, the Areca identification step extracts shape and color features as inputs for the Convolutional Neural Network algorithm. The process evaluates the system's performance, providing a comprehensive assessment of the entire areca classification process.

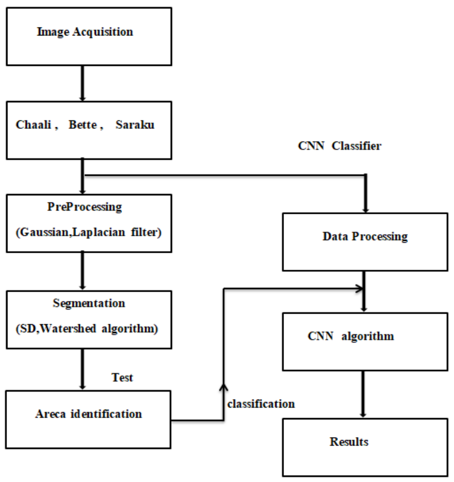

Fig. 1: Block diagram of Arecanut classification

3.2. Image acquisition system

The Arecanut images are captured by iphone13 mobile camera and DSLR digital camera. The iphone is capable of taking high quality images. This unit involves color camera with zooming lens and its resolution is 3024 x 4032 dimensions. Here, three different types of arecanut are captured by mobile and digital camera. The three types are Chaali,Bette and Saraku.

Fig. 2: a) Typical images of Bette, it is processed areca nut, and they are of any shape.
b) Typical images of Chaali, peeled areca round in Shape.
c) Typical images of Saraku, boiled areca nut and it is in any shape.
d) Typical images of areca nut slices and they are of any shapes.
e) Single areca nut images of Bette, Chaali, Saraku.

3.2 PreProcessing

The different preprocessing steps are:

3.2.1 RGB to Gray Scale conversion

The process of RGB to gray conversion of images uses "rgb to gray ()" function. This function transforms the image from color to grayscale by removing color information and retaining only the light intensity of each pixel. Grayscale images are represented by 8-bit pixels, allowing for 256 different shades of gray to be displayed.

Fig 3: RGB to Gray Arecanut image

3.2.2 Histogram Equalization

To increase the image's clarity, histogram equalization is used. By applying histogram equalization, the resultant picture achieves a more balanced distribution of pixel intensities, leading to increased contrast and enhanced visibility of details. This technique helps to overcome issues like underexposure or overexposure, where certain regions of that picture may appear too dark or too bright.A pixel's intensity levels can range in number from 0, 1, 2, 3….. (L-1). L $= 2^m$ Here m represents the amount of pixel bits necessary to encode the various intensities. Entire black or dark is represented by zero level intensity, whereas entire white or the absence of grayscale is represented by L-1 level.

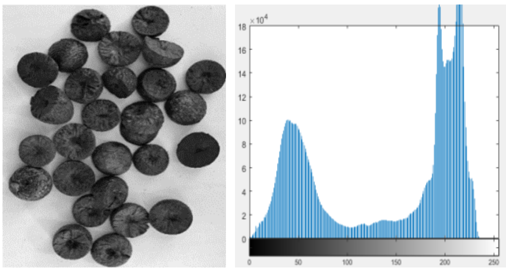

Fig. 4: Histogram before and after equalization

3.2.3 Denoising

Denoising is the process of decreasing or eliminating picture noise. Laplacian and Gaussian filters are used in this work to eliminate the noise.

a) Gaussian Filter

The fspecial () function utilized for implementing the Gaussian filter. This filter is implemented by convolving the input picturing a Gaussian kernel. The weighted mean of the pel values surrounding each pixel is subjected to the Gaussian filter. The kernel used for this operation is a square matrix with odd dimensions. Using a Gaussian filter featuring a kernel size of [11x11] is employed for low pass filtering to eliminate scattered light reflections from the picture.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)} \qquad (1)$$

Where G(x, y) is the measurement of Gaussian filter at coordinates (x, y).The Gaussian distribution's standard deviation is denoted by σ. The Low Pass Gaussian filtered image is depicted in Fig. 5.

Fig. 5: Image with filtering by Gaussian filter

b) Laplacian

Laplacian filter is employed to improve certain features in the GLP filtered image. The laplacian filter is often utilized for decreasing noise in arecanut images. Laplacian filter can be applies on arecanut images by using locallapfilt (I,sigma,alpha) function. Using the values of sigma=0.5 and alpha=0.05.The laplacian of an image highlights the regions of rapid intensity change.

The laplacian filter can be expressed in equation (2)

$$\nabla^2 G = \frac{\partial^2 G}{\partial x^2} + \frac{\partial^2 G}{\partial y^2} \qquad (2)$$

Where G denotes the Gaussian Low pass filter image. Laplacian filtered Image is displayed in Fig.6

Fig. 6: Image with filtering by Laplacian filter

3.3 Segmentation

The method of segmenting an image involves breaking up into different regions. This process is usually used to identify objects or other significant elements in an image data.

3.3.1 Standard Deviation:

In Image processing, standard deviation represents a metric used in statistics to reveal data about the amount of variation or dispersion in pixel values within a specific region of an image. This is frequently used to assess how much of noise present in an image.

Let μ be the expected value (the average) of random variable X with density f(x):

$$\mu \equiv \mathrm{E}[\mathrm{X}] = \int_{-\infty}^{+\infty} x\, f(x)\ dx \tag{3}$$

The standard deviation σ of X given by

$$\sigma \equiv \sqrt{E[(X-\mu)^2} = \sqrt{\int_{-\infty}^{+\infty} (x-\mu)^2 \quad f(x)}\ \mathrm{dx} \tag{4}$$

$$\sigma_{mean} = \frac{1}{\sqrt{N}}\sigma \tag{5}$$

Here N represents the number of observations inside the sample used to calculate the mean. Mean value is the sum of pixel values split by the entire number of pixel values.

se = strel('disk', windowWidth, 0);

J = stdfilt(I, hood) calculates the local standard deviation of the source picture I.

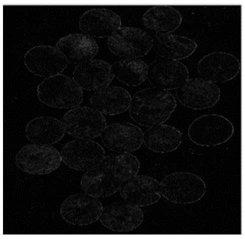

Fig. 7: Image segmentation by standard deviation

3.3.2 Watershed algorithm

In this work, the watershed () function utilized to investigate a particular method. Instead of the original grayscale image, the gradient magnitude image is utilized for watershed transform's input which is determined by filtering the original grayscale image to reduce noise. Distance transformation is then used to assign each pixel value representing its distance to the nearest edge. This is essential when defining the flooding process within the watershed technique. The distance transform produces a picture, which is then transformed with the watershed algorithm. Initially focusing on the edges shown in the gradient magnitude image, the flooding process effectively fills basins and boundaries. This method uses the image as a surface, where light pixels indicate high points and dark pixels represent low points, to identify catchment basins and the watershed ridge line.

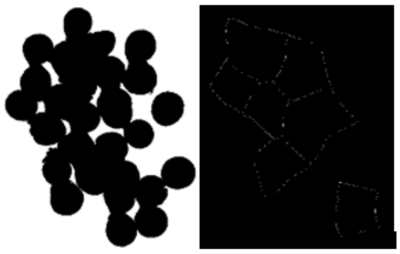

Fig. 8: Thresholding image and watershed ridgelines

4. Classification

Using training data with a known class label, classification is a technique for identifying the class of a new observation. Training and testing are the two steps of this. Once the features are extracted, a classification algorithm is hired to classify the arecanut images into three different classes. There is numerous classification methods available, which includes conventional machine learning algorithms alternatively, deep learning fashions like convolutional neural networks (CNNs) may be applied to analyze complicated styles and make predictions based totally on the extracted features.

Convolutional Neural Network: A Convolutional Neural Network (CNN) is a effective deep learning version specially designed for processing and reading structured grid-like data, which include images and motion images. CNNs use filters, additionally referred to as kernels, to analyze shared features via combining facts throughout different spatial dimensions or channels. A series of deep convolutional layers are used to learn and extract these characteristics. CNNs include pooling layers in addition to convolutional layers to speed up the data flow and simplify the representation. For instance, max pooling entails examining a matrix of images pixels, generally in a 2x2 window, and deciding on the maximum activation cost within that region. This pooling operation reduces the spatial dimensions while keeping the presence of essential functions. In the final stage, the pooling layer's output offers a scalar price that denotes the presence of a particular feature.

A fully connected or dense layer with the same range of neurons as the number of classes in the task is frequently included in the final layer of a CNN. This layer creates predictions by categorising a picture into distinct groups using the knowledge gained from the preceding levels.

5. RESULTS AND DISCUSSION

In this work, we tested for three cases. In all three cases we got different accuracy values. For the classification of Bette, Chaali and Saraku we considered 600 single images of three distinct arecanut species. Each type consists of 200 images, bringing the total to 600. The dataset was split into a training set and a testing set in an 80:20 ratio. The training set consists of 160 photos, each of which has been categorized as one of three different categories. Each types remaining pictures were reserved in the evaluation dataset. We trained the instance of 20 epochs initially, but we also investigated for 50,100 and 300 iterations. In all cases, the model's precision was 98%.

Accuracy and loss graphs provide a visual representation of the model's performance during of each training and testing phases. The accuracy graph demonstrates the improvement of accuracy over epochs, whilst the loss graph illustrates the decreasing fashion of model errors. The testing and training dataset accuracy and loss variance for the models used in the current study are shown in the graphs below.

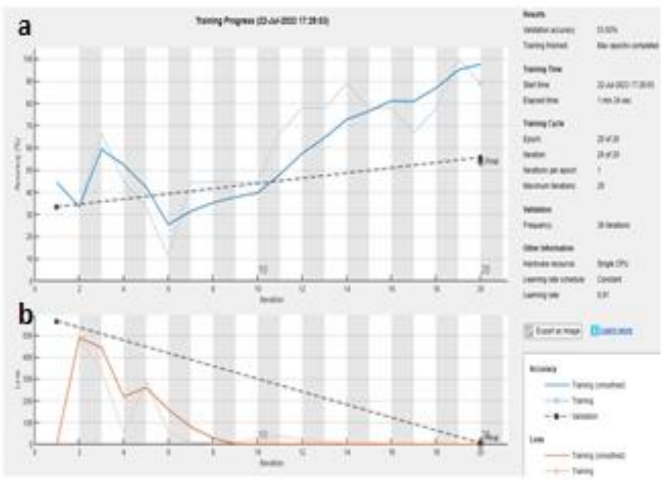

Fig. 9: a) Graph of accuracy VS Epoch and b) Graph of Loss VS Epoch

The analysis of train network usage shows the analysis of how much train network usage is consumed by each layer in a CNN. The source picture dataset is indicated in a format of 256 x 256 x 3 pixels, where 3 indicate the three color channels. The raw input is then placed through a variety of layer operations by the CNN, including convolution layers, pooling layers and fully connected layers. Each layer performs a different operation based on the input image. The analysis illustrates that the convolution layers consume most of the train network usage, followed by the fully connected and the pooling layers. This is because the convolution layers are the most computationally expensive portions of the CNN. They perform convolution operations on the input image, which requires a lot of computation. The fully connected and layers of pooling are lower complicated expensive, but they still consume a significant amount of train network usage. This analysis used to enhance the CNN.

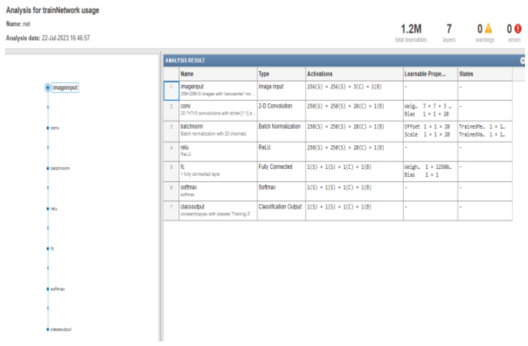

Fig. 10: Analysis for train network usage

The number of observations for each combination of true and anticipated classes is displayed in a confusion matrix. This matrix is commonly visualized by shading the elements according to their value. Diagonal elements (the correct classification) are shaded in one color and the other elements (the incorrect classification) in another color. The categorization of arecanuts by CNN is demonstrated by the confusion matrix. The true species are defined as Bette (class 1), Chaali (class 2), and Saraku (class 3). The predicted classes from the CNN are also Bette, Chaali, and Saraku. For Bette images tested, there were 9 correct predictions, but there were no correct predictions for Chaali in column 1. This indicates that the CNN may find it challenging to differentiate between Saraku, Bette, and Chaali, as they have similar shapes. The third value in column 1 (15) represents the CNN's prediction as Bette for Saraku testing images. The reason for this is probably because Saraku and Bette are all similar in shape and colour. In column 2, the number 6 indicates correct predictions as Bette from Bette images, while the number 39 shows the CNN correctly predicted Chaali from Chaali images. The third value in column 2 (10) represents the CNN's incorrect prediction as Saraku for Saraku testing images. Similarly, in column 3, the number 25 represents correct predictions as Bette, and the value 1 indicates a correct prediction as Chaali. The number 15 in column 3 is the CNN's prediction as Saraku, which is likely due to the similarity in colour between Bette and Saraku. Overall, the matrix of confusion indicates that the CNN was able to classify the arecanuts with a high degree of accuracy. The similarities between the many different kinds of arecanuts, however, may be reason for some incorrect information.

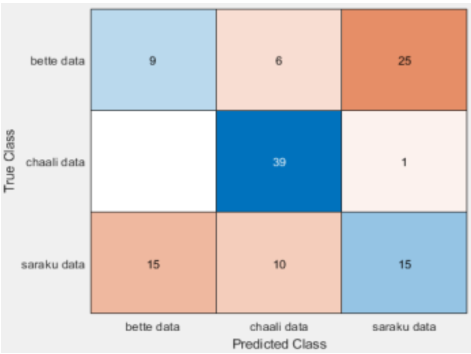

Fig.11: Analysis of the classification of three Classes using a confusion matrix

6. CONCLUSION

The primary objective of this classification process was to accurately identify and classify arecanuts using image processing techniques. To achieve this goal, a methodology involving image acquisition, preprocessing, segmentation and classification was employed. CNN algorithm is implemented to develop a classification model identifies three types of catechu. In this experiment, different Arecanut images were compared, and it was discovered that all of them performed well. In this work compare to adaptive and iterative threshold watershed algorithm best perform segmentation and hence identification. CNN regardless of noise, uneven illumination, with various backgrounds and random imaging accurately classifies the Areca types.

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