# Image analysis for classifying coffee bean quality using a multi-feature and machine learning approach

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**ABSTRACT**

Price and customer satisfaction depend on coffee bean quality. The coffee industry must analyze coffee bean quality. Global demand for robusta coffee is high. Coffee industry professionals mostly understand coffee bean quality. Thus, an image analysis using a computer vision-based approach for classifying robusta coffee bean quality is required. Image acquisition, region of interest (ROI) detection, pre-processing, segmentation, feature extraction, feature selection, and classification are covered in this study. A multi-feature derived based on color, shape, and texture features was employed in feature extraction, followed by feature selection using principal component analysis (PCA). Several machine-learning methods classified the coffee beans. The method performance was assessed using precision, recall, and accuracy. The selected features using the backpropagation neural network (BPNN) classifier outperformed others with 98.54% accuracy.



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## 1. INTRODUCTION

The utilization of computers and associated technologies is seeing fast expansion and diversification. The application of this is being observed in the field of agriculture. There exist multiple instances wherein computers have been employed in the agricultural sector, encompassing the monitoring of fruit ripeness [1], [2], land management [3], and plant development [4], [5]. Coffee, as one of the most widely consumed beverages globally, holds significant importance as an economic commodity. The global popularity of coffee can be attributed to its stimulating properties and the preference for its bitter flavor. Coffee serves as a substantial provider of caffeine for a considerable number of individuals. While previous research has established a connection between coffee and caffeine intake and adverse health effects, recent studies have presented evidence suggesting that the compounds found in coffee, such as caffeine, chlorogenic acids, kahweol, cafestol, and various micronutrients (such as magnesium, potassium, and phosphorus), may enhance the immune system and provide protection against the development of conditions such as obesity, diabetes, neurological diseases, osteoporosis, and pancreatic cancer [6].

The coffee industry values quality because of the relationship between coffee bean scarcity, monetary compensation, and consumer happiness. Robusta coffee beans, widely grown, have a distinct taste and aroma. Quality of robusta coffee beans depends on soil makeup, climate, and processing method. Coffee prices depend on bean quality. It is crucial to note that not all growers and coffee shop owners can identify coffee bean quality. Thus, errors may occur when they lack this expertise. Grading is time-consuming and produces inconsistent outcomes. Due to visual perception limits, fatigue, and coffee quality evaluation differences, these inconsistencies occur. Visual characteristics are often used to evaluate robusta coffee beans. In this situation, computer vision may work. It extracts robusta coffee bean visual traits that highly predict quality. Color, form, and texture may be needed for this procedure.

Numerous research investigations have been conducted in computer vision, focusing on the application of food processing. These studies encompass a range of food items, such as banana [7], honey [8], date fruit [9], palm oil [10], and coffee [11], [12]. The construction of this system involves several general processes, namely pre-processing, segmentation, feature extraction, and classification [13]. Common pre-processing tasks often involve scaling [14] and converting color spaces [15]. The Otsu thresholding method [13], K-means clustering algorithm [16], and edge detection approach [17] were subsequently employed, along with many established segmentation methodologies. The extractable features that can be considered for edibles encompass color [10], shape [18], and texture [11]. Moreover, naïve Bayes (NB) [10], k-nearest neighbor (KNN) [19], and support vector machines (SVM) [10] are frequently utilized in the classification process.

Recent studies have used machine learning to classify coffee beans across agricultural situations. Color and shape helped identify high-quality beans. The investigation used image processing and machine learning on an Arduino mega board. Essential criteria were assessed to determine high-quality green coffee beans. KNN was used to evaluate coffee beans and classify them by defect type. Logic, image processing, and supervised learning algorithms are executed and coded on the Arduino board. The machine vision system has an average accuracy of 94.79% for quality and 95.78% for defect-type evaluation. However, long berry bean classification was 98.05% accurate [20]. Subsequently, a variety of machine learning methodologies such as SVM, deep neural networks (DNN), and random forest (RF) were utilized to evaluate the significance of shape and color characteristics in the assessment of faults in coffee beans. The data presented in the study highlights the significance of color descriptors in the classification of faults in coffee beans. The classification models consider the most significant features obtained from the average G value of the component in the RGB color space and the average V value in the HSV color space. All the classifier models exhibited comparable performance, with the best accuracy value above 88% [12].

Several efforts were presented in order to identify and categorize coffee fruits, as well as to map the stage of maturation of these fruits during the harvest process. The methodology was executed utilizing the Darknet framework. The YOLOv3-tiny object identification system identified and categorized coffee fruit. The collection contains 90 videos from the 2020 arabica coffee (Catuaí 144) harvest, shot at a coffee harvester's discharge conveyor termination point. A business area in Patos de Minas, Minas Gerais, Brazil hosted the recordings. The model performed best at around 3300th iteration with an 800×800-pixel image input. The model had 84% mean average precision (mAP), 82% F1-score, 83% precision, and 82% recall in the validation set. The precision values for unripe, ripe, and overripe coffee fruits were 86%, 85%, and 80%, respectively [21]. Another study used a convolutional network on an inexpensive micro-controller board to classify coffee leaf diseases locally without the internet. Early diagnosis of coffee plant diseases was crucial for optimal output and production quality. Two datasets and development board images were used in this investigation. The collection included around 6000 images from six sickness classes. The incorporated cascade and single-stage systems were 98% and 96% accurate, respectively. These findings imply that these structures detect coffee plantation diseases [22].

This study presents a proposed method for classifying coffee bean quality based on computer vision techniques. The method utilizes color, shape, and texture data extracted from the RGB, HSV, and L*a*b color spaces. The BP was employed as the classifier in this work. The objective of this method was to ascertain the classification of coffee beans according to their quality by utilizing image data. The quality types were classified into four classes: intact, perforated, wrinkled, and cracked.

## 2. MATERIALS AND METHODS

The approach predicted the quality class of all robusta coffee bean photos. Its main processes were region of interest (ROI) detection, pre-processing, feature extraction, selection, and classification. The method has two phases: training and testing. Training and testing sets provided input for each phase. Both phases were handled differently. ROI detection assigned the coffee bean area to the image using K-means clustering. The training step pre-processed RGB data into grayscale, HSV, and L*a*b. Afterward, color, texture, and shape were used to extract features. Subsequently, the feature selection procedure was used to choose the most significant features and simplify classification. Pre-processing merely converted RGB to the feature selection color space during testing. Principal component analysis (PCA) generated the selected features in the proposed technique. The feature selection result was used to apply the extracted feature. A prediction class (intact/perforated/wrinkled/cracked) was determined from selected features in the final step. Figure 1 illustrates the robusta coffee bean quality classification.

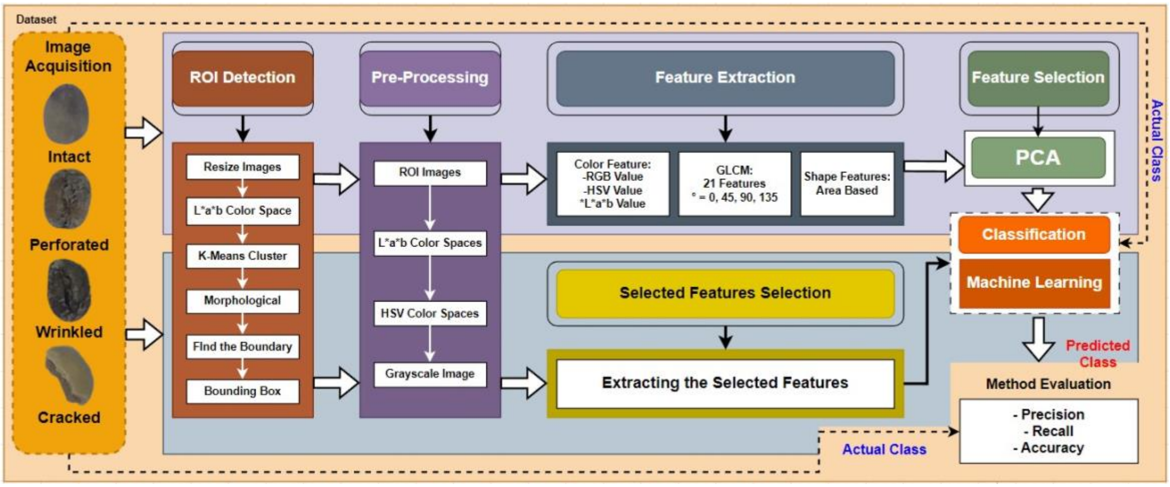
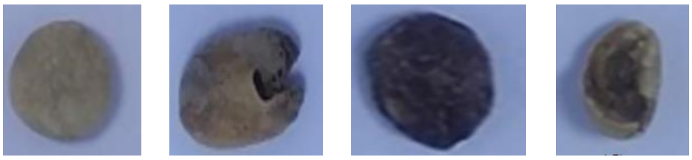



Figure 1. Overview of all steps in the proposed method for quality classification of robusta coffee bean

## 2.1. Dataset

The dataset in this study was images of robusta coffee beans. JPEG images were taken with a Xiaomi 5A smartphone's inbuilt camera. The coffee bean was placed on a white background in the center of a 28×19×18 cm studio minibox. A 10 cm gap between the camera and the coffee beans was maintained by deliberately positioning and orienting the camera. Smartphone cameras are 13-megapixel. The image has dimensions of 1560×1560 pixels. The dataset had 1440 coffee bean images, 360 each class. It was divided into four classes: intact, perforated, wrinkled, or cracked, with the example image shown in Figures 2(a) to 2(d), respectively.



(a) (b) (c) (d)

Figure 2. Examples of coffee bean images with various quality types: (a) intact, (b) perforated, (c) wrinkled, and (d) cracked

## 2.2. Region of interest detection

ROI detection attempts to generate a sub-image mostly of the coffee bean area. During this stage, the initial resolution of the image was reduced from 1560×1560 pixels to 500×500 pixels [3] to minimize the computational time. Subsequently, a color space conversion was performed from RGB to L*a*b; this enabled the system to accurately differentiate between object and background regions in various scenarios. The utilization of L*a*b color spaces necessitates a conversion procedure that relies on the values within the RGB color space, which are explicitly defined as in [23].

The result of the conversion of an original image in RGB Figure 3(a) to L*a*b color space is depicted in Figure 3(b). Furthermore, by employing the clustering with the K-means algorithm [16], the area of coffee beans was approximated. Due to the division of the image's area into two distinct regions—the coffee bean region and the background region—the value of K was set into two. The steps of the K-means algorithm are defined as follows [24]:

– Step 1: initialize number of cluster k and centre.
– Step 2: For each pixel of an image, calculate the Euclidean distance d, between the centre and each pixel of an image using the relation given.

$$d = ||p(x,y) - c_k|| \quad (1)$$

– Step 3: Assign all the pixels to the nearest centre based on distance d.
– Step 4: After all pixels have been assigned, recalculate new position of the centre using the relation given:

$$C_i = \frac{1}{k}\sum_{y\epsilon c_k}\sum_{x\epsilon c_k} p(x,y) \tag{2}$$

– Step 4: Repeat the process until it satisfies the tolerance or error value.
– Step 5: Reshape the cluster pixels into image.

The resulting image of the K-means algorithm is shown in Figure 3(c). Afterward, a morphological operation was applied using dilation; hence, the coffee bean area approaches the original, and the result is depicted in Figure 3(d). Subsequently, the setting of the coffee bean area was carried out as the ground for defining the ROI image boundary based on the yellow box, as shown in Figure 3(e). Accordingly, the formed ROI images in binary and RGB color space are shown in Figures 3(f) and 3(g).


Figure 3. The resulting image of each process in ROI detection: (a) original image in RGB color space, (b) L*a*b color space, (c) K-means clustering, (d) morphological operation, (e) setting the area of ROI image, and (f) ROI image

## 2.3. Pre-processing

This procedure generated parameter values for feature extraction. This study examined color, texture, and shape. RGB images must be converted to L*a*b and HSV to create color features, RGB images to grayscale to create texture features, and binary images to build form features. In order to improve classification results, the color space must be changed during pre-processing. Agricultural research uses RGB for object classification. Some investigations have employed L*a*b and HSV color spaces. Using different color spaces requires a conversion technique that uses RGB values [23]. In (3)-(6) define RGB-to-L*a*b conversion. In HSV color space, in (3)-(4) calculate hue (H) and then saturation (S) and value (V). S and V values were computed using as (5) and (6).

$$H = \begin{cases} \theta, & B \le G \\ 360 - \theta, & B > G \end{cases} \tag{3}$$

where:

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[x(R-G)^2+(R-B)(G-B]^{1/2}}\right\} \tag{4}$$

$$S = \begin{cases} 0, & \max(R,G,B) = 0 \\ 1 - \frac{\min(R,G,B)}{\max(R,G,B)}, & otherwise \end{cases} \tag{5}$$

$$V = \max(R,G,B) \tag{6}$$

Furthermore, converting the RGB image to a grayscale image was needed; hence, this work applied texture features. These feature parameters will later be used as input for the classification process. RGB conversion to grayscale is carried out to produce intensity (I) values using (7) [11].

$$I = \frac{1}{3}(R+G+B) \tag{7}$$

## 2.4. Feature extraction

Coffee bean image feature extraction retrieves color, texture, and shape information. Some studies analyze one aspect, while others analyze several. This study analyzes three approaches for extracting three-color features using RGB, HSV, and L*a*b color model statistical values. RGB, HSV, and L*a*b are useful color characteristics in many applications. Converting RGB to HSV and L*a*b limits color space dimensions and features. Texture feature extraction using the gray level co-occurrence matrix (GLCM) follows. Our form feature extraction approach uses statistical characteristics and shape distance in the binary picture. Table 1 lists method feature counts. Adding features doesn't necessarily enhance model performance. Thus, accurate classification requires careful feature selection.

Table 1. The number of features

| Type of features | Method | Number of Features |
|---|---|---|
| Color | RGB Model | 3 |
| | HSV Model | 3 |
| | L*a*b Model | 3 |
| Texture | Statistic Feature of GLCM | 84 |
| Shape | Area-Based | 2 |

#### 2.4.1. Color feature extraction

The HSV, RGB, and L*a*b color spaces have been used as color features to differentiate various objects [11]. In (8) uses the mean to examine each color model channel's statistical properties. Where μ is the average color channel. This study seeks HSV, RGB, or L*a*b feature extraction methods for coffee bean data analysis. This study got red, green, and blue color values from the RGB image, hue, saturation, and value values from the HSV image, and lightness (L) and color-opponent dimensions (a and b) indicating redness–greenness and blueness–yellowness from the L*a*b image.

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_{ij}) \tag{8}$$

#### 2.4.2. Texture feature extraction

Coffee bean textures can be identified by texture. Coffee bean fiber has distinct visual and texture properties. The color characteristics of the perforated, wrinkled, cracked class are similar to those of the intact class, making identification difficult. Only GLCM is used to extract texture features in this investigation. GLCM has been used for texture feature extraction with good results.

Calculating the probability of the adjacency relationship between two pixels at a specific distance and angle orientation yields GLCM [1]. Calculate the image's statistical attributes after collecting the co-occurrence matrix. GLCM statistical features exist for four angles (0°, 45°, 90°, and 135°) and one distance (1 pixel). GLCM (*i*, *j*) is the joint probability distribution of a pixel pair with gray levels *i* and *j*. Image gray level determines GLCM matrix rows and columns. *L* is the computed gray levels minus 1. The grayscale value of an image between 0 and 255 [7]. The types of features used in GLCM in this research include: auto correlation, cluster prominence, cluster shade, contrast, correlation, difference entropy, difference variance, dissimilarity, energy, entropy, IDM, information measures of correlation 1, and 2, inverse difference, maximum probability, sum averages, sum entropy, sum of squares variances, sum variance, IDM normalized, inverse difference normalized.

#### 2.4.3. Shape feature extraction

The k-means method was employed to convert the coffee beans image into a binary image in order to remove noise in the shape of the coffee bodies. The goal of the K-means algorithm is to cluster objects by grouping them with the K points that are closest to them in the space. The values of cluster centroids are updated iteratively until the optimal clustering results are achieved. Various shape parameters, such as eccentricity (e) and perimeter (p), are calculated to assess the characteristics of coffee bean shape [20].

$$e = \sqrt{1 - \frac{b^2}{a^2}} \tag{9}$$

$$p = 2\pi\sqrt{\frac{(a^2+b^2)}{2}} \tag{10}$$

### 2.5. Feature selection

The analysis should consider the total amount of features in order to identify the most beneficial or highly discriminative features within the utilized dataset. The present study employed PCA as a method for conducting feature selection. PCA is a well-established technique in the field of pattern recognition and computer vision. It serves as a standard method for feature extraction and data representation, commonly employed to identify and recognize objects. A statistical method reduced the number of dimensions in data sets with many factors. It makes object recognition work better and has been shown to lower and raise the accuracy value [25].

### 2.6. Classification

Data is classified by classification. Machine learning has several plant objects uses. By researching algorithms and using data to forecast, machine learning automates operations. The algorithm uses a model to estimate data and make judgments based on sample input instead than following fixed instructions. Mathematical and statistical models predicted unknown data using training data. This study classified coffee bean quality using machine learning. Backpropagation neural network (BPNN), linear discriminant analysis (LDA), KNN, NB, and SVM were used. Previous research on numerous plant specimens used these methodologies [19], [25].

### 2.7. Performance measurement

Feature selection and different classification approaches are used to evaluate the proposed method's performance and determine the most appropriate and robust method for the data set. This study evaluates 1140 robusta bean photos (360 intact, 360 perforated, 360 wrinkled, and 360 cracked). The performance of the classification method was assessed using three indicators: accuracy [25], which were calculated based on the multiclass confusion matrix. The parameters are defined by (11) [25].

$$Accuracy = \frac{correct\ number\ of\ data}{total\ number\ of\ data} \times 100 \tag{11}$$

## 3. RESULTS AND DISCUSSION

The total number of 1440 images consisted of four classes, including intact, perforated, wrinkled, and cracked, used to evaluate the method. The classification results were compared for feature sets obtained without and with feature selection. The feature set without feature selection was performed using the features formed by GLCM, which were area-based and color-based (RGB, HSV, and L*a*b). The selected features were applied to PCA. The experiment utilized five classifiers: BPNN, KNN, LDA, NB, and SVM. The method's performance was assessed using accuracy. The comparison of method performance with different classifiers using multi-feature indicated by the accuracy value is summarized in Table 2.

Table 2 demonstrates the testing of situations without feature selection. The tests were conducted using texture characteristics obtained by the GLCM approach, texture data combined with shape features (Area-based), and texture features combined with HSV, L*a*b, and RGB color spaces. The BPNN classifier achieved the maximum accuracy of 94.83% while utilizing the GLCM. Subsequently, the LDA, KNN, SVM, and NB classifiers yielded decreasing accuracy values of 92.08%, 85.21%, 83.54%, and 80.83%, respectively. The BPNN classifier achieved the maximum accuracy of 97.86% for the area-based feature set, while the NB classifier had the lowest accuracy of 58.54%. The performance relied on color attributes derived from three color spaces: HSV, L*a*b, and RGB. The performance of the approach utilizing HSV showed that SVM attained an ideal accuracy rate of 92.92%. Using the L*a*b and RGB feature sets, the BPNN achieved an impressive accuracy rate of 97.71%.

Table 2. Performance comparison of the classifier with various feature sets based on accuracy value (%)

| Classifier | Without features selection | | | | | With features selection |
|---|---|---|---|---|---|---|
| | GLCM | Area Based | HSV | L*a*b | RGB | PCA |
| BPNN | 94.83 | 97.86 | 84.79 | 97.71 | 97.71 | 98.54 |
| KNN | 85.21 | 84.38 | 85.42 | 90.83 | 89.79 | 90.83 |
| LDA | 92.08 | 91.46 | 77.92 | 91.46 | 68.33 | 80.63 |
| NB | 80.83 | 58.54 | 53.96 | 53.54 | 48.54 | 55.83 |
| SVM | 83.54 | 72.71 | 92.92 | 97.50 | 94.83 | 97.50 |

In the results obtained via PCA feature selection, the backpropagation classifier attained the maximum accuracy value of 98.54%. By contrast, the NB classifier yielded the lowest results, achieving an accuracy of 55.83%. Backpropagation demonstrates high accuracy across all feature test situations without requiring feature selection. The LDA algorithm achieved the highest accuracy rate of 98.54% across all four test scenarios. It was performed using the GLCM feature, Area-based method, HSV color space values, and PCA application for feature selection. The NB classifier is consistently overwhelmed by every trial situation. The observed results indicate that a combination of texture, shape, and color features, followed by feature selection to limit the number of features, might lead to high accuracy throughout the classification process. The BPNN classifier performs better than other classifiers by minimizing errors in each scenario.

## 4. CONCLUSION

This study classifies robusta coffee beans by quality. There are four types of coffee beans: intact, perforated, wrinkled, and broken. This procedure involves ROI detection, pre-processing, segmentation, feature extraction, selection, and classification. Each step is done to accurately classify coffee beans and determine their quality. The study tested designs with texture, texture with shape, and texture with color space values (HSV, L*a*b, and RGB). BPNN study routinely outperforms other coffee bean quality assessment methodologies. It uses the PCA feature selection technique to get the best results on GLCM, area-based, and L*a*b features with 98.54% accuracy. Using several scenarios and attributes can improve the variety and quality of this research.

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