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Cocoa bean quality identification using a computer vision-based color and texture feature extraction

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ABSTRACT

The current pressing issue in the downstream processing of cocoa beans in cocoa production is a strict quality control system. However, visually inspecting raw cocoa beans reveals the need for advanced technological solutions, especially in Industry 4.0. This paper introduces an innovative image-processing approach to extracting color and texture features to identify cocoa bean quality. Image acquisition involved capturing video with a data acquisition box device connected to a conveyor, resulting in image samples of Good-quality and Poor-quality of non-cutting cocoa beans dataset. Our methodology includes multifaceted advanced pre-processing, sharpening techniques, and comparative analysis of feature extraction methodologies using Hue-Saturation-Value (HSV) and Gray Level Cooccurrence Matrix (GLCM) with correlated features. This study used 15 features with the highest correlation. Machine Learning models using Support Vector Machine (SVM) with some parameter variation value alongside an RBF kernel. Some parameters were measured to compare each approach, and the results show that pre-processing without sharpening achieves better accuracy, notably with the HSV and GLCM combination reaching 0.99 accuracy. Adequate technical lighting during data acquisition is crucial for accuracy. This study sheds light on the efficacy of image processing in cocoa bean quality identification, addressing a critical gap in industrial-scale implementation of technological solutions and advancing quality control measures in the cocoa industry.

1. Introduction

Cocoa bean quality identification is a vital component of the cocoa industry, significantly influencing the quality of end products such as chocolate. The processing of cocoa beans requires strict adherence to established quality the final products meet consumer expectations and regulatory requirements. Evaluation of dried cocoa beans at the farm level often shows considerable variability, leading to inconsistencies in product quality. In chapter III, the Federation of Cocoa Commerce (FCC), in its publication related to physical characteristics in cocoa industry quality requirements, visually shows some characteristics of Poor-quality cocoa beans [1]. The cocoa processing industry and the FCC standards indicate that ensuring that the cocoa beans received are consistent is very important. Two of the indicators of cocoa bean quality are color and texture. The color of cocoa beans can reflect the level of maturity, cleanliness, and other conditions that affect the product's final quality. Therefore, developing an automated approach to cocoa bean quality control is very important. Using computer vision systems in conveyor systems in the downstream cocoa processing industry can effectively overcome these challenges. Generally, modeling of a detection system based on computer vision and machine learning

(ML) begins the process where cocoa beans are taken from farmers from various region sources, depending on the research conducted, for example, research by Zhinin-Vera *et al.* examined the quality of cocoa beans from Ecuador [2], Eric *et al.* studied of cocoa beans from Ghana [3], Obediencia *et al.* conducted a survey of cocoa beans from Philippine [4], Lopes *et al.* studied cocoa beans from several South and Central American countries [5], including from Indonesia by several related studies [6], [7]. Although the studies conducted by each are different, the data source comes from cocoa farmers and dry cocoa bean data is used similarly.

Computer vision technology has the potential to automatically monitor and identify the quality of cocoa beans at the production facility. Automated surveillance systems enhance efficiency, accuracy, and productivity in various industries. The application of computer vision in industrial production processes has been the subject of extensive research, aiming to improve quality control, monitoring, and surveillance. Integrating computer vision technologies into industrial-scale research endeavors aimed at automating product surveillance systems holds substantial promise for augmenting efficiency, quality control, and monitoring across diverse industries. Raw material management is essential for smooth production operations and upholding product quality benchmarks. Akindipe's research underscored the importance of efficient raw material management within production operations [8], and research by Wulansari *et al.* emphasized the importance of raw material availability in sustaining industrial viability. As the cornerstone of the manufacturing process, the availability of raw materials directly affects the sustainability and productivity of industrial businesses [9].

The use of data in image processing in several studies, there are indeed two models that have been used, namely the cut-test data model [3], [4], [7], [10], where the cocoa bean object was split and then captured as a dataset for further processing. The next cocoa bean data model that is also widely used in related research is the non-cutting test model research [2], [5], [11]–[14], where the cocoa object was captured directly from the shape of the beans with the shell. The use of the data model, of course, adjusts to the research conducted by each researcher. However, following the needs of the early-stage industry where the collection of cocoa beans from farmers entering the industry is no longer through the cut-test but through visual observation of the beans still with the shell, this study uses a dataset with the form of cocoa beans data with the shell (non-cutting test). The cocoa bean object is captured using a camera to produce static image data for processing. This research used video acquisition data extracted into images to be processed using the same subsequent image processing system [2] but with a different approach and analysis system. As several studies have been done, the core of the research process was carried out in the quality identification system. The approach model is based on state-of-the-art and consists of selecting image processing techniques, feature extraction, and classification techniques. Current methods for assessing cocoa bean quality primarily rely on manual inspection, which can be subjective and prone to human error. Additionally, these traditional techniques may not adequately capture the diverse quality attributes present in cocoa beans, such as color, texture, and moisture content. This variability poses challenges for producers and processors, as it can result in suboptimal quality control and economic losses.

The application of machine learning models in quality identification, in general, has been widely applied, mainly based on research that utilizes conveyor systems as data acquisition tools, such as the detection system for sorting passion fruit [15], detection of large foreign objects on coal mine belt conveyor [16], and identifying and screening out various large foreign objects [17], [18]. The identification process generally uses monitoring that is expected automatically, utilizing an electronic circuit system connected to a computer vision system and machine learning so that the final product can classify objects according to the scheduled system objectives. Several studies related to the cocoa beans non-cut-test dataset [2], [5], [11], [12], [19], have shown that the urgency of raw material product quality is a potential area for integration with computer vision modeling. A proper computer vision approach, technical aspects, and a prototype approach will streamline the identification process. Therefore, based on the background of the problem and the potential research in the field of computer vision, it is proposed that the contributions of this paper are as follows: 1) The innovative cocoa bean quality assessment employs computer vision with a pre-processing approach aimed at simplifying the development of prototypes within the industry; 2)The effectiveness of image processing techniques for automated cocoa bean quality control is evaluated by analyzing feature extraction parameters and suitable classification techniques. The parameters include the technical aspects of designing a data capture model with a conveyor equipped with a data acquisition box; 3) The implementation of OpenCV algorithms facilitates precise analysis of cocoa beans. This contribution includes a program structure equipped with a short pseudocode when wanting to implement the results of this research in the same case or different instances.

The identification results can automatically manage the cocoa bean selection and grouping process in the cocoa manufacturing industry. This approach is expected to improve efficiency and consistency in the cocoa bean selection process, resulting in a high-quality final product. This study aims to fill this gap by employing advanced computer vision techniques to automate quality identification. By leveraging image processing and machine learning algorithms, this research seeks to provide a more accurate and consistent evaluation of cocoa bean quality, ultimately enhancing the efficiency of the cocoa supply chain. In addition, this study can also help reduce human error and increase productivity in the cocoa processing industry.

2. Method

Developing the quality detection system in this research used image processing techniques with a feature extraction system involving the color and texture of the object. As the general architecture of the quality detection system, the following system framework, as in Fig. 1, was implemented in this study.

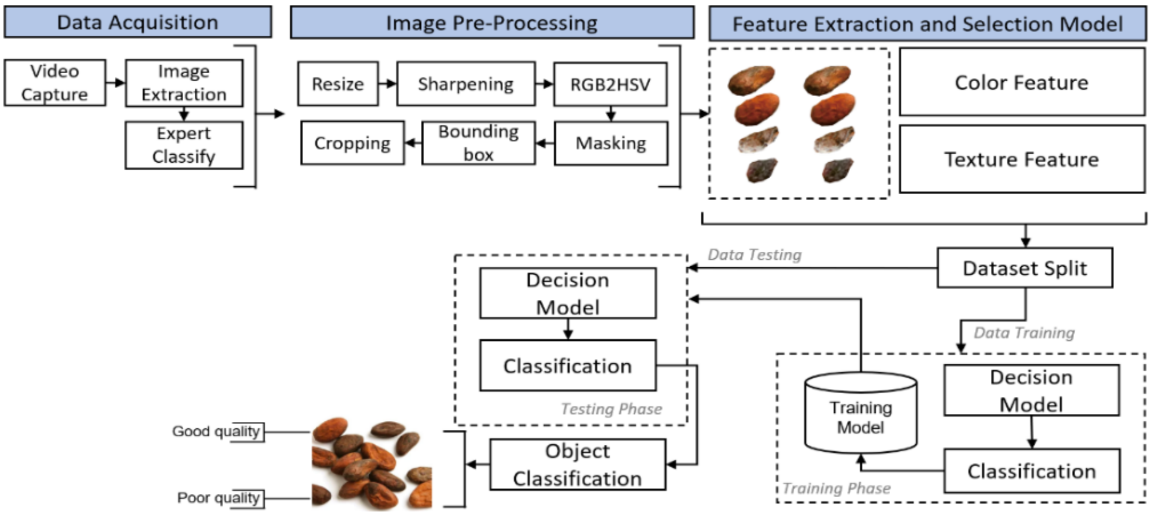


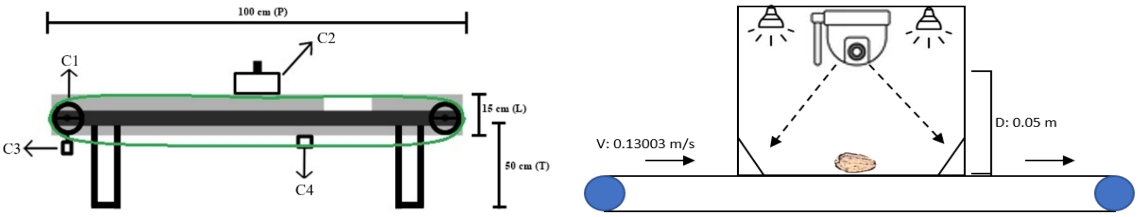
Fig. 1. Framework model

Image Processing was used for the classification process in this research, using Python programming version 3.10 with Jupyter Notebook Anaconda3 as the application interface. The explanation of each stage is in sections 2.1-2.5.

2.1. Data Acquisition

Data Acquisition in this study used a conveyor device specially designed using electronic devices, as shown in Fig. 2(a). This conveyor design was developed as an advanced prototype for the sorting system of good-quality and poor-quality cocoa beans as the data class in this study.

The conveyor is designed simultaneously as a quality classification prototype with a realized size of 100cm x 15cm x 50cm. The working concept based on the drawing code is that the DC Motor (C-3) will be connected to the pipe (C-1) so that the DC Motor (C-1) can move the conveyor belt (C-8). The cocoa beans will then pass through the image capture box (C-2) with a camera (C-6) to record the beans and LED lights to provide light. Then, the camera recorded the moving cocoa beans, and the recording data was processed on a laptop to be classified. Then, the servo motor (C-4) will move according to the results of the classification process. The dataset utilized in this study comprises a diverse collection of images of cocoa beans, categorized into Good and Poor-quality. This diversity is crucial as it encompasses variations in lighting conditions, backgrounds, and cocoa bean appearances, which reflect real-world scenarios. In this system, the conveyor moves the cocoa beans with a DC motor speed of 100 Rotary Per Minute (RPM) as the main drive of the conveyor belt so that the object of cocoa beans conditionally arranged per bean moves at an average speed of 0.13003 m/s, with a camera and belt distance of 0.05m. The camera used in this process is a Brio Ultra HD Pro Business Webcam 13 Megapixel, 4K/30fps camera. However, this dataset is adjusted to data collection with an image value of 1030x720 pixels. The lighting on the box uses an Evatech 5050 LED Strip with a range of 960-1,320 Lumens. The original images used in this study were 916, consisting of 458 images of Good and Poor-quality beans. The data was divided into good and poor-quality files while maintaining the file name during the processing of every image data. This conveyor design was developed as an advanced industrial prototype for the quality control of the cocoa bean sorting system. Fig. 2(b) illustrates the framework for the data acquisition box (C2).



(a) (b)

Fig. 2. Data Acquisition model, a. Conveyor design, b. Design of data acquisition box

The dataset of cocoa beans based on Good and Poor-quality processed by computer vision is an image of cocoa beans with a non-cut-test model, which means that the captured cocoa beans are cocoa beans with their shells. The cocoa beans sampled in this dataset were taken from dried cocoa beans in Landi Kanusuang village, Sulawesi Barat Province, with latitude: -3.33180 and Longitude: 119.17149. The original images used in this study were 916, consisting of 458 images of Good and Poor-quality beans. The data was divided into good and poor-quality files while maintaining the file name while processing every image data. The cocoa bean type comes from a cocoa bean clone named Sulawesi 1, with fermentation-based processing and drying standards condition (6.7% water content). Classification of cocoa bean quality classes in this study is based on image extraction results as shown based on the samples in Fig. 3.

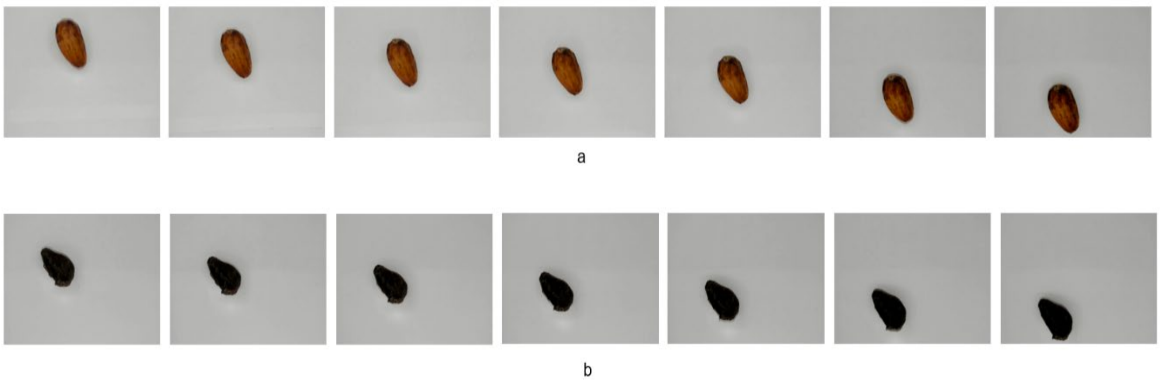


Fig. 3. Image of cocoa beans in some frames, a. Good-quality, b. Poor-quality

2.2. Pre-Processing

Data pre-processing was performed in seven stages after the image data was extracted from the video data capture using the Data Acquisition box.

2.2.1. Raw Extracted Cocoa Beans Image

As previously described, the Raw Extracted Cocoa Beans Image is obtained by extracting frames from the video taken from the data acquisition box of the designed conveyor.

2.2.2. Raw Extracted Cocoa Beans Image

The resized dataset undergoes a pixel size transformation from 1030x720 pixels to 960x540 pixels. A comparison of the object's Histogram pre- and post-resizing, along with the OpenCV algorithm, is illustrated in Fig. 4.

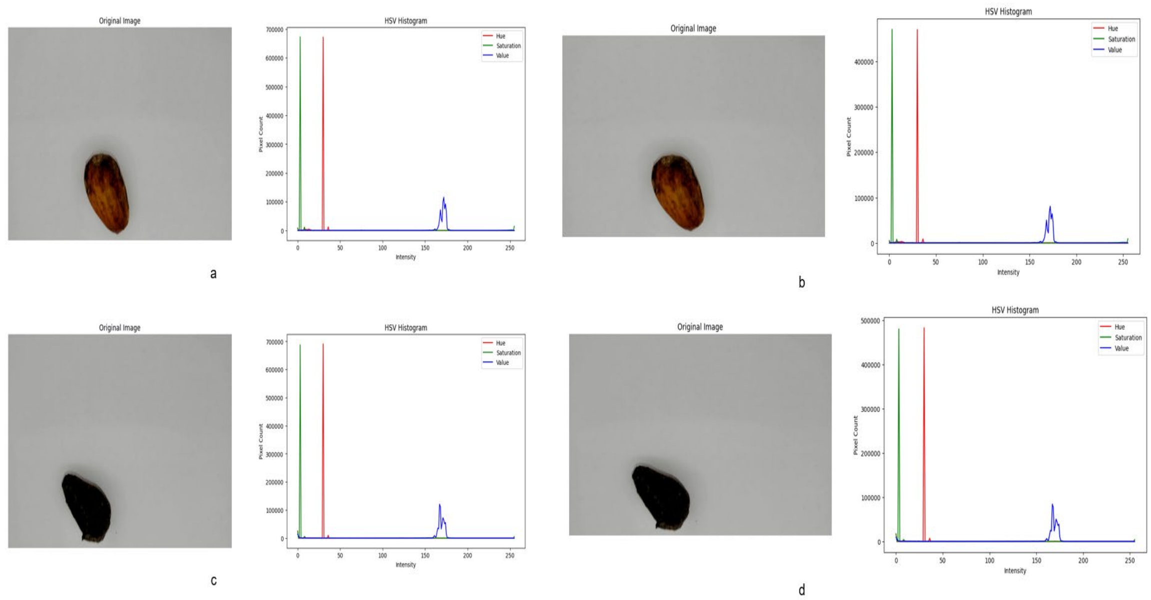


Fig. 4. Resizing of Cocoa Beans Image with Histogram, a. Good-quality Image raw 1030x720 pixel with Histogram, b. Good-quality Image raw 960x540 pixel with Histogram, c. Poor-quality Image raw 1030x720 pixel with Histogram, d. Poor-quality Image raw 960x540 pixel with Histogram

2.2.3. Sharpening Image

Sharpening cocoa bean images entails employing a convolution operation utilizing a 3x3 kernel. Within this kernel, the central value is notably higher (6) than the surrounding values (-1). This strategic configuration augments the contrast among pixels and enhances the finer details within the cocoa bean image. The sharpening formula based on convolution with a kernel can be expressed as the following equation.

$$g(x,y) = k \circledast f(x,y) = \sum_{m=-a}^{a} \sum_{n=-b}^{b} k(m,n) f(x-m, y-n) \tag{1}$$

where $g(x,y)$ is the output image, and $\circledast$ denotes the convolution operator [20]. This formula represents the sharpened intensity value at a pixel location (x,y) as a weighted sum of the neighboring pixel intensities, where $k(m,n)$ represents the convolution kernel coefficients. In Python, libraries like *NumPy* can be employed for array programming, offering efficient tools for managing multidimensional arrays and executing array operations [21].

2.2.4. Convert Image RGB to HSV

The process of changing RGB to HSV was done after sharpening so that the background pixels become homogeneous in pixel size so that when changes are made to HSV, the background will have visible color dominance. The HSV color space represents colors based on their Hue, Saturation, and Value components, providing a more intuitive representation for color-based image processing tasks. Conversion from RGB to HSV is standard in various image-processing applications. Several studies implemented this approach for image processing, like adaptive image enhancement [22], [23], fruit ripening stage prediction [24], and color intensity quantification [25]. RGB to HSV conversion is crucial in extracting meaningful color information from images. Additionally, the conversion to HSV (Hue, Saturation, Value) is imperative for many tasks, such as color recognition, color measurement [26], and obstacle height estimation. Preserving chromatic information and accurately representing colors are crucial for thoroughly analyzing and interpreting visual data across these diverse applications.

The algorithm converts the read image from the RGB color space to the HSV color space using OpenCV's *cv2.cvtColor()* function with the flag *cv2.COLOR_BGR2HSV*. Conversion RGB to HSV formula based on convolution can be expressed as the following equation [27].

$$H = arctan\left\{\frac{\sqrt{3(G-B)}}{(R-G)+(R-B)}\right\} \tag{2}$$

$$S = 1 - \frac{min(R,G,B)}{V} \tag{3}$$

$$V = \frac{R + G + B}{3} \tag{4}$$

where the RGB normalization process needs to be carried out following equations (5), (6)) when the value of H cannot be represented if S = 0 [28].

$$S = \left\{\frac{if(c==0)0}{else\frac{c}{V}}\right\} \tag{5}$$

$$H = \left\{\begin{matrix} if(c==0)0 \\ else\ if\ (V==R)1+\frac{G-B}{6c} \\ else\ if\ (V==G)\frac{2}{6}+\frac{B-R}{6c} \\ else\frac{4}{6}+\frac{R-G}{6c} \end{matrix}\right\} \tag{6}$$

2.2.5. Masking Image

The image masking process creates a mask based on the specified HSV value range. The purpose of masking is to separate the object from the background. The algorithm defines the minimum and maximum values for the hue, saturation, and value channels to establish the thresholds for masking, denoted as h_min, h_max, s_min, s_max, v_min, and v_max. Utilizing the $cv2.inRange()$ function, a binary mask is created, where pixels within the specified range are set to white (255), and those outside the range are set to black (0). Formula presentation-related pixel conversion to mask the image, as the following equation.

$$let\ h_{min}, h_{max} = 0{,}179 \tag{7}$$

$$s_{min}, s_{max}\ (P) = 25{,}255 \tag{8}$$

$$s_{min}, s_{max}\ (G) = 56{,}255 \tag{9}$$

$$v_{min}, v_{max} = 0{,}255 \tag{10}$$

where "P" denotes the Poor-quality dataset and "G" represents the Good-quality dataset. The lower limit values for saturation and value channels are critical in defining the thresholds for effective masking. For the Poor-quality dataset (equation 8), a saturation minimum of 25 is established to exclude pixels that are too desaturated, which may not represent the true color of the cocoa beans. This threshold ensures that only pixels with sufficient color intensity are considered, thereby enhancing the accuracy of the classification process. Similarly, for the Good-quality dataset (equation 9), a higher saturation minimum of 56 is set to capture the vibrant colors characteristic of high-quality cocoa beans. This distinction is essential for differentiating between the two datasets, as it allows the algorithm to focus on the most relevant features that signify quality. The hue range (equation 7) is set from 0 to 179, encompassing the full spectrum of colors in the HSV color space, while the value range (equation 10) is set from 0 to 255 to include all brightness levels. This comprehensive approach ensures that the masking process is robust and can accurately isolate the cocoa beans from varying backgrounds.

2.2.6. Merge Image Masking

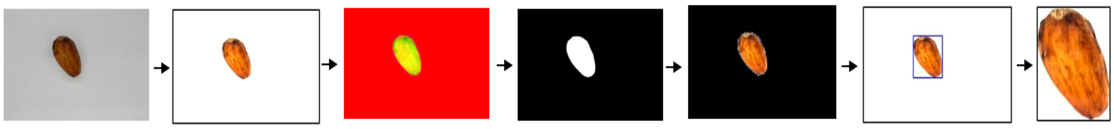
This stage was done by applying a mask to the image of cocoa beans that had been sharpened. The algorithm generally begins by iterating through each image file in the labeled directory. This process iterates for each image in the directory.

2.2.7. Bounding Box Object Image

The bounding box process was done to localize the pixel position of the image so that all the background will be dominantly removed and only the object will be left. The algorithm functions by iterating through each image file within the input directory, reading and converting each RGB image to the HSV color space. Thresholds are defined for each channel (Hue, Saturation, and Value) to create a mask. Contours are detected in the mask image, and if found, the algorithm selects the contour with the most significant area, likely corresponding to the desired object.

2.2.8. Cropping Object Image

This stage was done to find the most significant contour of the cocoa bean object, calculate the bounding box, and perform cropping on the original image based on the bounding box coordinates. Threshold values are defined for creating a mask based on the HSV image, followed by creating the mask function. The mask is then applied to the HSV image using bitwise operations, and contours are detected in the masked image to identify regions of interest. If contours are found, the algorithm selects the contour with the most significant area, indicative of cocoa beans. It determines the bounding box (x, y, width, height) of the selected contour, crops the original image based on this bounding box to extract only the cocoa beans, and saves the cropped image. The object produced in the pre-processing stage is visually shown in Fig. 5.



(a)

(b)

Fig. 5. Transformation image (Sharpening, masking, bounding box, and cropping), (a) Sampel of Good-quality cocoa bean, (b) Sampel of Poor-quality cocoa bean

2.3. Feature Extraction

As in Fig. 1, feature extraction in this research was done with two models: Hue, Saturation, and Value (HSV) for the color feature and Gray Level Cooccurrence Matrix (GLCM) for the texture feature utilized. GLCM is generally used to analyze an image's texture [29]. GLCM uses a matrix concept to describe the frequency of pixel pairs with varying intensities at specific distances and directions [30]. This method was widely applied in various cases ranging from pattern recognition [31], segmentation [32], and texture analysis [33]–[35]. This method has been widely applied in various research scenarios. However, the application to the research object for identifying cocoa bean quality, as this study by Adhitya *et al.* shown, is that GLCM has a more effective model than CNN in the feature extraction process [36]. Feature extraction with GLCM in this study applies contrast, energy, correlation, ASM, homogeneity, and dissimilarity features. GLCM defines a square matrix where the size indicates the probability of a gray value, $g1$, separated by a fixed spatial distance from another gray value, $g2$. Consider

$f(i,j)$ as a 2D grayscale image, where S represents the set of pixels with a specific spatial arrangement within the area, and P denotes the GLCM, which can be formulated as the subsequent equation.

$$P(i,j) = \frac{\#\{[(i_1,j_1),(i_2,j_2)] \in S \mid f(i_1,j_1)=g_1 \& f(i_2,j_2)=g_2\}}{\#S} \tag{11}$$

Implementing feature extraction with GLCM with OpenCV-based programming is made by computing Greycomatrix($img\_gray, distance, angles, normed = True, symmetric = False$). Distance and angles are defined to determine the relationship of pixels in GLCM.

Color feature extraction with HSV extracts the characteristics of cocoa bean objects in terms of color features. Various studies have explored the use of HSV for feature extraction. Research that applies HSV for color space on image objects, an example of a method used for this purpose is the Temporal Convolutional Network (TCN) algorithm, which was applied to identify the intensity of pain in facial images of hospitalized patients [37], including its implementation on fruit to measure its ripeness level [38]. Both studies provide color space specifications in images based on pixel values with Hue, Saturation, and Value spaces. The pattern of pixel values will facilitate identifying object characteristics in images based on color. These studies collectively demonstrate the potential of HSV for feature extraction in various applications. The feature extraction process using HSV in this research using OpenCV uses cv2.cvtColor(img, cv2.COLOR_BGR2HSV). The HSV average calculation was made using the HSV image. The combination of color feature extraction using HSV and texture features using GLCM has been applied to the research case of weaving fabric motif pattern recognition using K-fold cross-validation test classification with an accuracy of 91.67%. The combination of the two models is better than if they are only implemented unilaterally [39]. This study used 15 features with the highest correlation, namely value, saturation, hue, contrast 0°, contrast 45°, contrast 90°, contrast 135°, dissimilarity 0°, dissimilarity 45°, dissimilarity 90°, dissimilarity 135°, energy 0°, energy 90°, energy 45°, and energy 135°. Variations using all feature combinations were also tested in this study.

2.4. Classification

Support Vector Machine (SVM) selection in this study was evaluated to provide balanced predictive performance, even in studies with limited sample sizes [40]. This algorithm will classify Good and Poor-quality cocoa beans based on their features. In the Training Phase, SVM functions to classify the object's class, i.e., Poor-quality cocoa beans as class (0) and good cocoa beans as class (1), and store it as a data model to be compared in the testing phase. The training procedure for SVM classification begins by establishing input features (x) and target data (y). Subsequently, parameter values C and γ are set, with some variation value alongside an RBF kernel. This study used RBF as the kernel because the data used was non-linear, so a kernel must map the feature vector into a high-dimensional space. The computation of the kernel value follows a prescribed equation.

$$k(x_i, x_j) = exp\left\{\frac{||x_i,x_j||^2}{2\sigma^2}\right\} \tag{12}$$

where x_i= training data set and y_i= class label of x_i. The input data will be used to find the optimal α value using the Quadratic Programming equation in the following equation

$$\min_{\alpha} \frac{1}{2}\alpha^T P\alpha - q^T\alpha \tag{13}$$

where $P = y_i y_i k(x_i x_j)$, $k = (-\gamma \; ||x - x'\;||^2).\gamma$, q = vector with $N * 1$ (where N = number of training data), A= target, $b = 0$, G= lower limit α value, $G = 0$, h=upper limit of α value, $h = C$. After obtaining the optimal α value, find the optimal bias value for the test process with the following equation

$$\mathrm{b} = \frac{1}{N_s}\sum_{j=1}^{N_s}(\; y_j - \sum_{i=1}^{N}\alpha_i y_i xi^T x_{j_A}) \tag{14}$$

where y_i= target of the j^{th} support vector (where $j = 1 \dots Ns$), x_i=features of support vector, x_j= features of the training data, α_i= The optimal α obtained from Quadratic Programming, Ns= the number of support vectors, N= number of training data, and y_i= target of the training data.

As in previous research that used SVM as a classification technique to compare several feature extractions in the case of cocoa pod disease identification, the SVM classification process is generally the same as the research process conducted in general [33]. The difference in the research was the Grid Search stage in determining the value of parameters C and γ as in [41],[42], where the range of values for the combination of parameters is $C = [1, 10^1, 10^2, 10^3]$, and $\gamma = [10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}]$ for further accuracy. Iteration to get the best parameters continues with the most optimal parameter values C and γ from all parameter combinations that have been done.

2.5. Evaluation Matrix

Cocoa bean quality used Receiver Operating Characteristic (ROC) analysis for performance evaluation [43]. The resulting ROC curve illustrates the ability to separate the predicted distribution of the classifier from the two classes of poor-quality cocoa beans (Class 0) and good-quality cocoa beans (Class 1). The ROC matrix produces numbers in the form of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which are then used as calculations of Accuracy, Precision, Sensitivity, and F1-Score, as follows:

$$Accuracy(ACC) = \frac{\sum TP + \sum TN}{\sum Total\ population} \tag{15}$$

$$Precision(PPV)(y) = \frac{\sum TP}{\sum FP + \sum TP} \tag{16}$$

$$\text{Recall (y)} = \frac{\sum \text{TP}}{\sum \text{TP} + \sum \text{FN}} \tag{17}$$

$$F1\ score(y) = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{18}$$

where True Positives (TP) are classes (1) that are correctly predicted as class (1), True Negatives (TN) are classes (0) that are correctly predicted as class (0), False Positives (FP) are classes (0) that are incorrectly predicted as class (1), and False Negatives (FN) are classes (1) that are incorrectly predicted as class (0). In addition, the depiction in the form of area Under the Curve (AUC) ROC is also a valuable metric for quantitatively evaluating the model's performance.

3. Results and Discussion

3.1. Pre-Processing Analysis

The dataset created in this paper shows data appropriately processed according to the Computer Vision method contained in OpenCV, which explains the procedure. Further data processing will undoubtedly adjust to its use in machine learning or the application of Deep Learning or better models in the future. Referring to Fig. 6, which shows the Extracted Cocoa Beans Image with Histogram, there is no significant pattern difference in Hue and Saturation, except for the Value pattern. This process was influenced by reducing pixel count in the new resolution. Likewise, there is a change in the Histogram pattern when the sharpening process is performed, where the RGB2HSV process is performed on the object, it can be seen that the previous sharpening process makes the white background slightly grayish by the color of the Conveyor belt to be white, then by the RGB2HSV process, the white color is converted to red color homogeneously. In comparison, the average cocoa bean object shows distinctive characteristics, where for Cocoa Beans, Good-quality tends to be dominantly yellow, while for Cocoa Beans, Poor-quality tends to be green in color. This condition indicates a distinctive feature that can be processed further if the researcher wants to measure the damage to the beans from the dataset. The algorithm outlined in this paper can be readily applied for subsequent analysis or utilized as a framework for similar studies. Dataset analysis for pixel degradation and image treatment measures the pre-processing model's potential to reduce computational load. Fig. 6 shows a drastic average pixel decrease in the RGB color space, indicating a significant reduction until the final cropping stage.

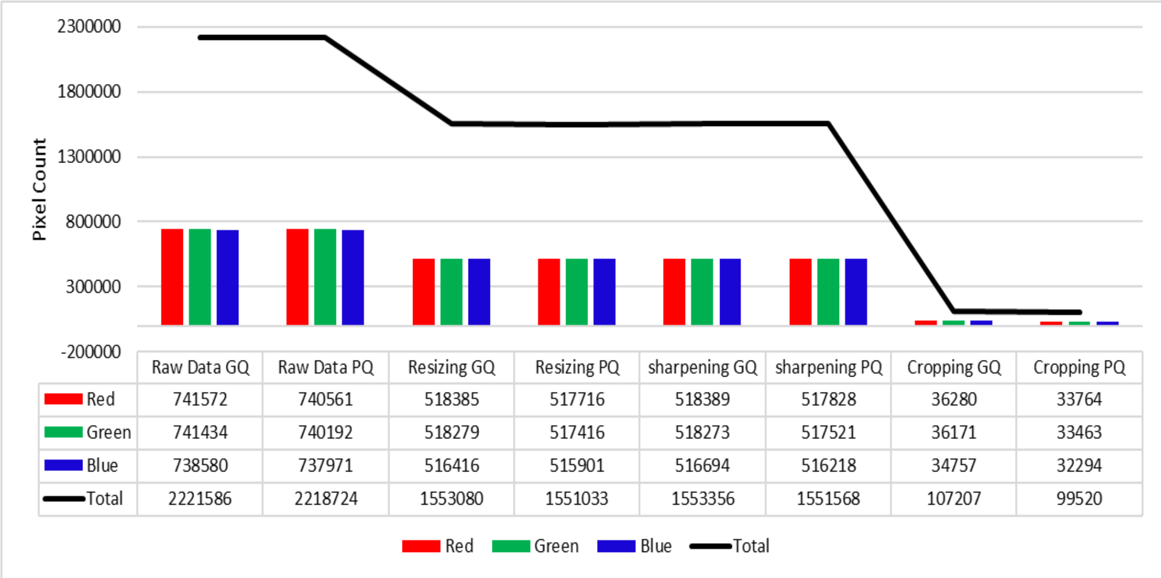


Fig. 6. Pixel Count Analysis Result of Cocoa Beans Image in Pre-processing Step

3.2. Classification Analysis

Based on three approaches at the pre-processing stage carried out as described in section 2.2. In this study, the results of the approach are shown in Table 1.

Table 1. ROC performance

Approach/ Feature Implementation	P0	P1	R0	R1	F0	F1	Acc
Non-Pre-Processing							
All features	0.96	0.86	0.90	0.95	0.93	0.92	0.92
15 features	0.91	0.84	0.85	0.91	0.88	0.87	0.88
Pre-Processing with Non-Sharpening							
All features	0.99	0.98	0.99	0.99	0.99	0.99	0.99
15 features	0.99	0.97	0.97	0.99	0.98	0.98	0.98
Pre-Processing with Sharpening							
All features	0.99	0.96	0.97	0.98	0.98	0.97	0.97
15 features	0.98	0.95	0.96	0.98	0.97	0.97	0.97

[a.] P=Precision, R=Recall, F=F1-Score, Acc=Accuracy, 0=Class Poor-quality, 1=Class Good-quality

Based on Table 1, the highest accuracy is observed in the Pre-processing without Sharpening condition approach, utilizing the default application of all features from both HSV and GLCM in the OpenCV system used in this research. Comparing all features and the 15 main features applied in this study shows that using all extracted features is better than only applying 15 correlated features from HSV+GLCM when pre-processing, with the highest accuracy of 0.99. This outcome implies that when discerning between Good and Poor-quality cocoa beans in this investigation, it is better to apply all HSV+GLCM features rather than only 15 correlated features. This indicates that the model is effective in classifying cocoa beans. In addition, the pre-processing applied in the study by sharpening the image failed to give much better results, although the accuracy value was not too far off. This result shows that the lighting at the time of data collection with lamp illumination with lumens values in the range of 960-1,320 used in the data collection box already provides sufficient lighting, so the sharpening process will only disturb the feature patterns of color and texture. The non-pre-processing approach was tested to evaluate the performance of the computer vision system against the two feature extractions combined in this study without pre-processing intervention. Using all features from the HSV and GLCM, we obtained Grid Search results according to the parameters in SVM with the best value at $C = 1{,}000$

and $\gamma = 0.01$) while using 15 features with the best value at $C = 10$ and $\gamma = 0.1$. The F1-Score value for class 0 is 0.93, and class 1 is 0.92, indicating a good balance between precision and recall. When utilizing only 15 features, the F1-Score value for class 0 reaches 0.88, while for class 1, it reaches 0.87. The pre-processing approach for experimental design was tested without sharpening to evaluate the performance. It can be seen that using all features from the HSV and GLCM feature extraction process results in a very high accuracy of 0.99. The use of all features from the HSV and GLCM feature extraction process obtained Grid Search results according to the parameters in SVM with the best value at $C = 10$ and $\gamma = 0.1$, while the use of 15 features obtained with the best value at $C = 100$, and $\gamma = 0.1$. The F1-Score value for both classes is also very high at 0.99, indicating an excellent balance between precision and recall.

Meanwhile, when using only 15 features, the F1-Score for both classes was 0.98. Another pre-processing approach with sharpening was tested to evaluate the performance of the computer vision system. The use of all features from the HSV and GLCM obtained Grid Search results according to the parameters in SVM with the best value at C = 10 and γ = 0.1, while the use of 15 features obtained with the best value at C = 100, and γ = 0.1. The F1-Score value for class 0 is 0.98, and class 1 is 0.97, indicating a good balance between precision and recall. Meanwhile, when using only 15 features, the F1-Score for both classes was 0.97. Based on the results of the analysis, it can be concluded that for both approaches, the feature extraction process produces good accuracy, which is 0.97. The study findings demonstrate that the computer vision system necessitates pre-processing, particularly when capturing image data from video-based cameras. Compared to the existing cases in the literature, such as [2] using YOLOv5 and [19] using the Deep Learning Model, which reported accuracy of 94.5% and 97%, respectively, our model shows a significant improvement. This enhancement can be attributed to our approach's advanced feature extraction techniques, which allow for a more nuanced understanding of the characteristics that define cocoa bean quality.

The implications of these findings are substantial; by implementing our model, stakeholders in the cocoa supply chain can achieve more consistent quality assessments, ultimately leading to better product quality and increased consumer satisfaction. Graphical representations of the AUC depicted in Fig. 7, Fig. 8, Fig. 9 consistently demonstrate positive outcomes, exceeding the designated threshold.

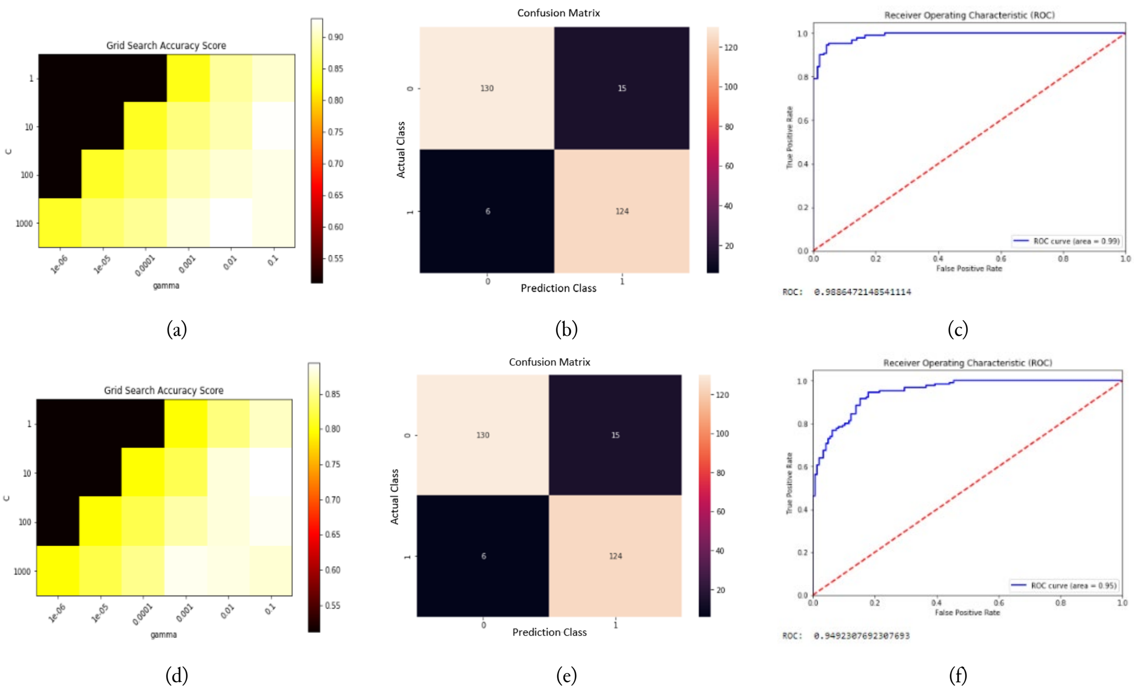


Fig. 7. Non-Pre-processing performance, (a) graphic from grid search all feature, (b) Confusion matrix all feature, (c) AUC Graphic all feature, (d) graphic from grid search 15 feature, (e) Confusion matrix 15 feature, (f) AUC graphic 15 feature

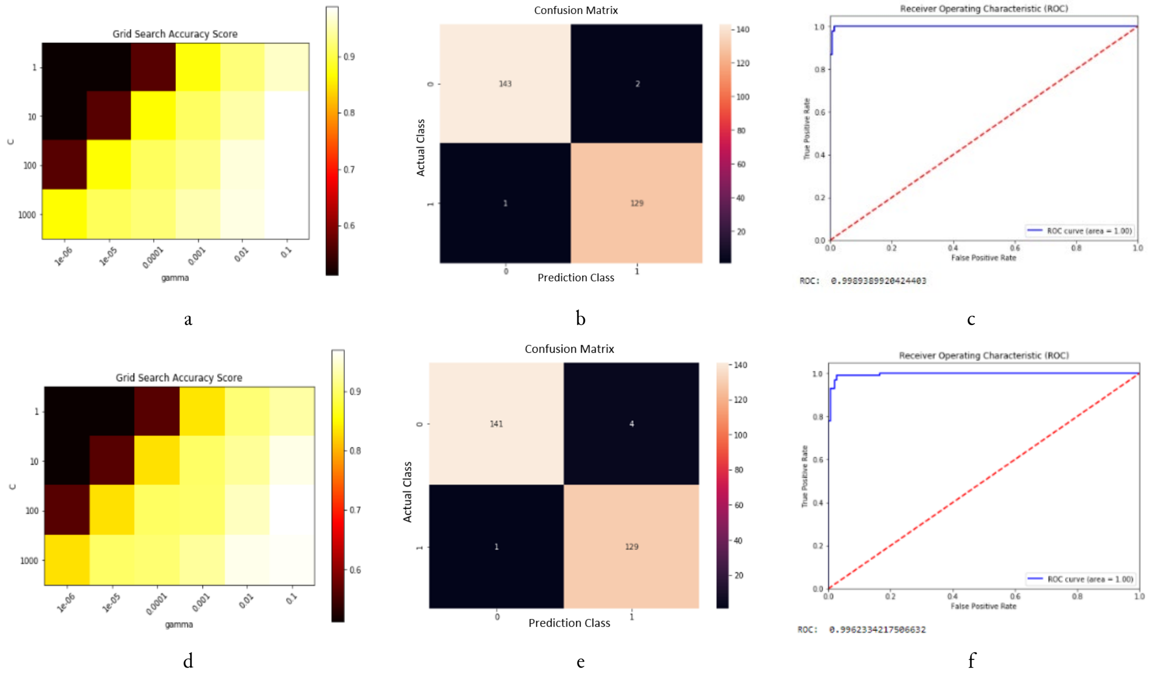


Fig. 8. Pre-processing (non-sharpening) performance, (a) graphic from grid search all feature, (b) Confusion matrix all feature, (c) AUC Graphic all feature, (d) graphic from grid search 15 feature, (e) Confusion matrix 15 feature, (f) AUC graphic 15 feature

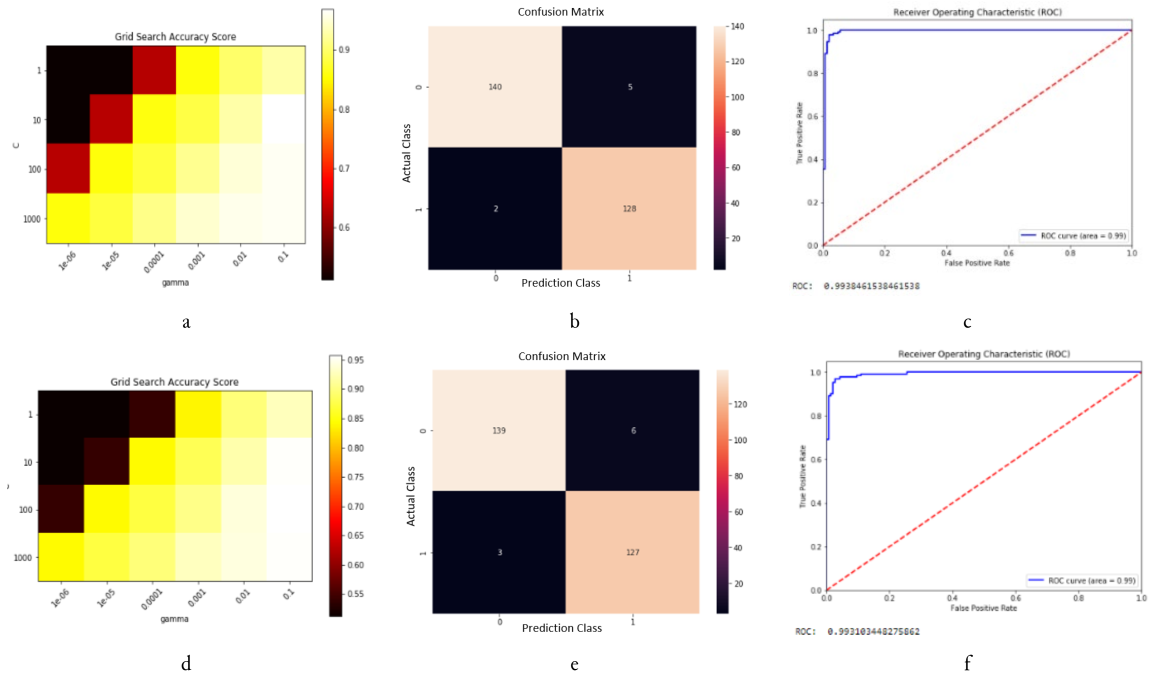


Fig. 9. Pre-processing (Sharpening) performance, (a) graphic from grid search all feature, (b) Confusion matrix all feature, (c) AUC Graphic all feature, (d) graphic from grid search 15 feature, (e) Confusion matrix 15 feature, (f) AUC graphic 15 feature

This result implies that the classification model by the AUC graph illustrates the model's ability to effectively differentiate between these classes, with a notably higher true positive rate than the false positive rate. The results of this graph indicate strong performance in classification endeavors. Based on the evaluation conducted compared to research with the same dataset model but with different methods or approaches, as in Table 1, the results of this study are still better based on the evaluation parameters using ROC. A further development that is a weakness that needs to be studied is the reliability in terms of computation time. This issue needs to be considered for further study to explore real-time systems more deeply. The research approach with the creation of a localized data acquisition box system with sufficient lighting will be able to contribute from the computational aspect, so there is no need to apply the sharpening algorithm, which will undoubtedly have an impact on the computational process when this research is used on an industrial scale.

This study offers several contributions and potential for industrial implementation in cocoa bean processing. Firstly, by leveraging computer vision techniques and OpenCV algorithms, the study demonstrates a robust methodology for cocoa bean quality assessment based on color and texture features. This innovative approach provides a reliable and automated means of evaluating cocoa bean quality, addressing the current challenges posed by manual assessment methods. Secondly, developing a comprehensive dataset comprising images of Good-quality and Poor-quality cocoa beans facilitates the training and validation of machine learning models, paving the way for the implementation of automated quality control systems in cocoa processing facilities. Additionally, the study highlights the importance of computational efficiency by reducing pixel count during image pre-processing stages, accelerating processing times, and enhancing overall system performance. This computational ease is crucial for seamlessly integrating computer vision technology into cocoa processing operations, promising increased productivity, cost savings, and improved efficiency. The research offers practical solutions for enhancing cocoa beans' raw material product quality and streamlining production processes.

4. Conclusion

This study introduces an implementation strategy for a Computer Vision System to classify cocoa bean quality using color and texture features acquired through a data acquisition box integrated with a conveyor system. The feature extraction model with some pre-processing approach was applied and compared using the ROC parameter. Based on the ROC analysis findings, we can conclude that pre-processing without the sharpening method achieves the highest accuracy in distinguishing between Good and Poor-quality cocoa beans. Especially when using all extracted features from the HSV+GLCM combination. A comparison between all features and 15 correlated features of GLCM showed the superiority of using all features in achieving the highest accuracy, which is 0.99. In addition, capturing data with an acquisition box and a lighting device shows that accuracy performance is not significant when applying the sharpening method to the image, indicating that adequate lighting during the data capture process is crucial. For future advancements, it is essential to assess the reliability of computation time, especially in real-time system deployments. One proposed solution is to consider creating a localized data acquisition system with adequate illumination to avoid sharpening algorithms and reduce the computational complexity required. The dataset used for training and testing the model may not fully represent the diversity of cocoa beans from different geographical regions, which could impact the model's generalizability, so future work could focus on expanding the dataset to include a wider variety of cocoa beans from different regions, which would enhance the model's robustness and applicability.

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Declarations

Author contribution. Basri: Conceptualization, Investigation, Methodology, Software, Validation, Writing an original draft, Writing review & editing. Indrabayu Indrabayu: Supervision, Conceptualization, Investigation, Methodology, Validation, Writing review & editing. Andani Achmad: Supervision, Validation, Writing review & editing. Intan Sari Areni: Supervision, Validation, Writing review & editing.

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Additional information. No additional information is available for this paper.

Data and Software Availability Statements

The datasets involved in this paper are available in the following information:

- Repository name: Mendeley Data [44]
- Data identification number: 10.17632/sr279sf4hs.1
- Direct URL to data: https://data.mendeley.com/datasets/sr279sf4hs/1

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