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Image-Based Classification of Robusta Coffee Roasting Degree Using LDA–KNN with Color and Shape Features

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ABSTRACT

The determination of robusta coffee roast levels is commonly conducted through visual assessment, which is inherently subjective and prone to inconsistency due to overlapping visual characteristics between adjacent roasting stages. On the other side, objective measurement equipment is often costly and not easily accessible. This study addresses this problem by proposing a digital image–based classification method for five robusta coffee roast levels (green, light, medium, medium-dark, and dark). Parameters included color feature extraction from RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), and shape features including area, perimeter, and circularity are extracted from captured images. A hybrid Linear Discriminant Analysis (LDA) and K-Nearest Neighbor (KNN) classifier with Manhattan distance is employed to enhance class separability and improve classification accuracy. Model performance was evaluated using a confusion matrix (precision, accuracy, recall and F-1 score). Results showed that by integrating multiple visual features and employing a hybrid classification strategy, the proposed approach was able to improve the classification of Robusta coffee roasting levels. The evaluation using a 90:10 data split with an optimal k = 16 resulted in the highest accuracy of 83%.

1. INTRODUCTION

Coffee is one of the most important agricultural commodities globally, with significant economic value and widespread consumption. Indonesia is the fourth-largest coffee producer in the world, producing approximately 11.3 million bags during the 2024/2025 period (USDA, 2024). Today, coffee has become a deeply ingrained part of daily life. In Indonesia, robusta coffee is often preferred by tasters for its color and body compared to arabica, making it widely used by businesses (Priyanto *et al*., 2022). Common roast levels are light roast, medium roast, medium dark roast, and dark roast. Roasting degree significantly influences the physical and visual characteristics of coffee beans, which are closely related to product quality (Bahrumi *et al*., 2022).

Visual methods that are often used by business actors are subjective, leading to inaccuracies in determining the level of roasting. Ultimately, this leads to inconsistent taste due to the lack of a validated system. Roast level can be examined by the Agtron scale (Yeager *et al*., 2022); however, this equipment requires a considerable cost. On the other hand, image processing which offers a means to classify roasting levels and has been extensively used in various coffee research studies with different algorithms.

Image processing has been widely applied in many research areas, such as for grading the quality of raw coffee (Bedaso *et al*., 2022), distinguishing between Robusta and Arabica coffee beans (Lumagui *et al*., 2020), differentiating the maturity levels of coffee beans (Dermawan *et al*., 2023), and detect the defect of coffee beans (Maghfirah &

Nasution, 2022). Saputra *et al*. (2024) utilized color features (HSV) and achieved excellent accuracy when classifying three roasting levels. Prastyaningsih & Kusrini (2021) found that the HSV color feature provides greater accuracy than $L*a*b*$. Wibawa *et al*. (2021) have gained an accuracy of 76% in classifying two roasting levels using RGB and HSV color features.

Another notable parameter is shape, which captures the physical attributes of coffee beans and contributes to improved discrimination between different roast levels. This multidimensional feature integration provides a more comprehensive representation of both color changes and the bean's physical characteristics. Previous studies have primarily focused on limited roasting categories or single feature types, which may not adequately capture the complexity of multi-class roasting classification.

In this study, the mean values of each color feature were reduced using LDA, resulting new features for enhance inter-class discrimination and the robustness of the classification process. This study also used KNN as the algorithm because it is highly robust to large datasets with significant noise. This algorithm has already assisted in classifying coffee bean quality, detecting defects, identifying roasted bean varieties, and classifying coffee leaf diseases, each with an accuracy exceeding 90% (Abuhayi & Mossa 2023; Huang *et al*. 2024; Jumarlis *et al*. 2022; Mujidah & Agustin 2024). This research aims to develop a system for quickly and accurately determining the roasting degree through digital image processing. This system will simplify determining the assessment level of roasting that ultimately to expense reduction for business scale.

2. MATERIALS AND METHODS

2.1. Materials and Tools

The materials used were Robusta green coffee beans obtained from Lampung coffee farmers through dry processing. The roasting levels were determined by the roastery at PT. Kemenady. Coffee images were captured from Robusta coffee beans in its green form and beans roasted at four different degrees: light roast, medium roast, medium dark roast, and dark roast. Therefore, there are five labels or categories, which are green, light, medium, medium dark, and dark. Each image contains 20 beans; thus, 80 images per class resulted in 1600 individual bean samples after segmentation. Four roasting degrees plus one level green coffee beans resulted a total 8.000 samples. The tools used were a mini studio, a Logitech camera with a resolution of 4096 × 2160 pixels, four 9 W LEDs, a duplex board, and a Lenovo spire Lite 14 laptop. The system was developed in the Phyton environment using the OpenCV library.

2.2. Research Methods

Research was conducted from June to September 2025 at two locations. The roasting process took place at the Science and Technology Park of Bogor Agricultural Institute. At the same time, image acquisition for all coffee categories was performed at the Food Processing and Agricultural Product Engineering Laboratory, IPB University. The stages of this research include roasting, image dataset acquisition, image segmentation, and digital image processing (Figure 1).

2.2.1. Image Acquisition

Images were captured using a Logitech camera connected to a laptop inside an image recording box (67.5 × 50 × 79.5 cm^3). A color calibration chart was used as a visual reference during image acquisition to ensure consistent illumination and camera settings across all samples. All images were captured in the same condition using the same camera and lighting conditions. The camera was mounted 10 cm above the object base. Lighting was provided by four 9W LEDs positioned at the four corners of the box. Autofocus was set to 30 and white balance adjusted to 5600K. Frames were composed of 20 coffee beans from each category, arranged in a 10 × 2 matrix with 2 cm gaps between samples (Ahmad & Nurrahman, 2023). Images were taken from the convex surface of the coffee beans. The arrangement of the apparatus for image acquisition is shown in Figure 2. A total of 80 images were acquired for each roasting category. Each frame received labeling that incorporated both the designated roast degree code and its sequential capture order. The coding scheme designated green as *G*, light as *L*, medium as *M*, medium dark as *MD*, and dark as *D*.

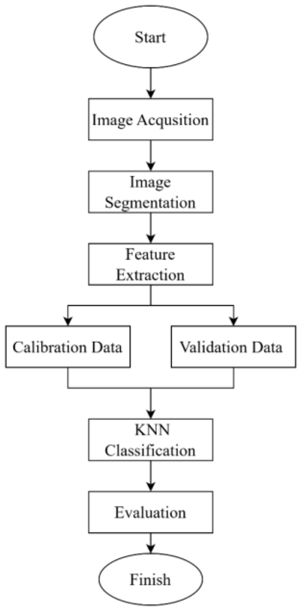

Figure 1. The research stages

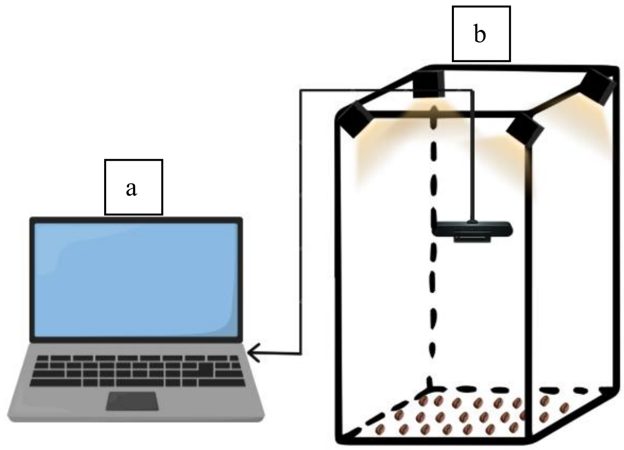

Figure 2. Image acquisition: (a) Laptop, (b) Recording box

2.2.2. Pre-processing

The collected images were transferred to Google Colaboratory for segmentation to separate the objects from the background. Object detection (coffee beans) was achieved by capturing objects with an area of at least 1000 pixels. Objects smaller than 1000 pixels were not considered coffee beans. Background separation was performed using the Threshold Binary Inverse method with a threshold value of 220. Based on study of Desiani *et al*. (2021), basic binary thresholding demonstrates superior accuracy compared to Otsu and adaptive thresholding methods for retinal blood vessel segmentation. Therefore, using a fixed threshold value is appropriate given the controlled acquisition and distinct pixel intensity separation in this study. The segmentation result rendered the target objects in white, while the background appeared black. Detected objects were contoured and numbered sequentially from the left side of the top row to the right side of the bottom row as shown in Figure 3. The detected objects are precisely cropped using bounding box coordinates derived from contour analysis producing Regions of Interest (ROI) that preserve the original RGB color information from the source image. These color-authentic ROIs are saved and served as the basis for subsequent quantitative analysis of feature extraction.

Figure 3. Contoured object

2.2.3. Feature Extraction

The extracted features in this research include color features using RGB and HSV methods. Each object generates average values of Red, Green, Blue, Hue, Saturation, and Value, which are considered as the dataset for image processing. The HSV values are obtained from the conversion process of RGB values through the following equations:

$$V = \max(r,g,b) \tag{1}$$

$$S = \begin{cases} 0 & if\ V = 0 \\ \frac{V - \min(r,g,b)}{V} & if\ V > 0 \end{cases} \tag{2}$$

$$H = \begin{cases} 0 & if\ S = 0 \\ 60 \times \frac{g-b}{S \times V} & if\ V = r \\ 60 \times [2 + \frac{b-r}{S \times V}] & if\ V = g \\ 60 \times [4 - \frac{r-g}{S \times V}] & if\ V = b \end{cases} \tag{3}$$

Meanwhile, the extracted shape features from the object are area, perimeter, and circularity.

$$Area = \sum_{n=1}^{x} \sum_{m=1}^{x} bw_{\text{area}} \quad (x,y) \tag{4}$$

$$Perimeter = \sum_{i=1}^{N-1} d_i = \sum_{i=1}^{N-1} \mathrm{I}\, X_i - X_{i+1}\, \mathrm{I} \tag{5}$$

$$Circularity = 4\pi \frac{Area}{Perimeter^2} \tag{6}$$

After all color components were extracted from all classes, the values were normalised due to the different ranges of values of these components. This was done to give equal weight to each piece of data. The data is reduced using LDA which transform the original nine-dimensional feature set (*R*, *G*, *B*, *H*, *S*, *V*, perimeter, area, circularity) into four discriminant components (LD1-LD4). These four discriminant axes preserve the most discriminative information, effectively reducing feature dimensionality while enhancing class separation prior to classification. Data dimension reduction aims to clarify the separation between classes and reduce computation time through eigen value decomposition of within-class variance (S_W) and between-class variance (S_B).

2.2.4. Algorithm

The algorithm used to train data for classifying roast levels is KNN, which is one type of Supervised Learning algorithm. The majority class determines the classification of new instances among the k closest neighbors obtained from the training dataset (Figure 4). One common distance metric to measure similarity between test and training data is the Manhattan Distance, also known as City Block Distance. This metric calculates the distance between two points in an n-dimensional space by summing the absolute differences of their respective coordinates, reflecting movement along horizontal and vertical axes. Studies indicate that using Manhattan Distance for this calculation can improve classification accuracy by approximately 1–2% compared to Euclidean Distance (Setiawan, 2022):

$$d_{ij} = \sum W_k \left| X_{ik} - C_{jk} \right| \tag{8}$$

where *W is* total weight, *X* is test data, and *C* is training in the database.

Initially, each sample is represented by a feature vector derived from color and shape information. LDA is then applied to the training data to reduce feature dimensionality while maximizing class separability by minimizing within-class variance and maximizing between-class variance. The resulting transformation matrix is used to project both training and testing samples into a lower-dimensional discriminative subspace. In this study, it results in four new feature components that yield the sharpest class separation. Subsequently, KNN classification is performed in the LDA-transformed space by computing the Manhattan distance between a test sample and all training samples. These distances are subsequently sorted in ascending order, from the nearest to the farthest neighbors. The class label of a test sample is determined based on majority voting among its k nearest neighbors.

2.2.5. Evaluation

Model performance validation using the holdout validation technique. This technique divides the dataset randomly into training data (for calibration) and validation data (Baso & Risald, 2023). The division of all data into these two types of datasets is proportioned at 90:10, 80:20, and 70:30. System performance is evaluated using a confusion matrix displayed in an $n \times n$ table, where n is the number of classes for analysis. Generally, a 2 × 2 table is used, as shown in Figure 5. This evaluation identifies accuracy by including the accuracy, precision, recall, and F-1 Score values. The calculations are formulated as follows (Novtahaning *et al*., 2022):

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{8}$$

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

$$F\text{-}1\ Score = \frac{2\,(TP)}{2\,(TP)+FP+FN} \tag{11}$$

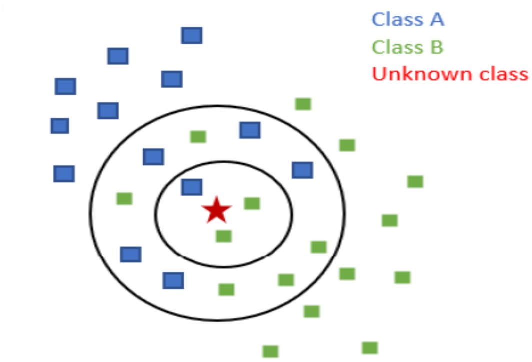

Figure 4. Illustration of KNN

		Actual Value	
		Positive	Negative
Prediction Value	Positive	TP	FP
	Negative	FN	TN

Figure 5. Confussion matrix

3. RESULTS AND DISCUSSION

The collected images have a resolution of 3200 × 1800 pixels and are stored in jpg format. Each category consists of 1600 images, results in a total 8000 data objects as illustrated in Figure 6. From each coffee bean image, color and shape features were extracted using the same region of interest (ROI) to ensure consistent pixel representation across samples. The extracted shape features include area, perimeter, and circularity, as shown in Figure 7. Color features were obtained from both RGB and HSV color spaces. The conversion from RGB to HSV is a pixel-wise transformation that does not alter the number of pixels, as defined in Equations 1–3. Consequently, identical pixel counts are preserved for both color spaces within each ROI. Figure 8 presents the distribution of mean color feature values across samples rather than pixel-level histograms; therefore, variations along the y-axis indicate the frequency of feature values among samples and do not reflect differences in the number of pixels.

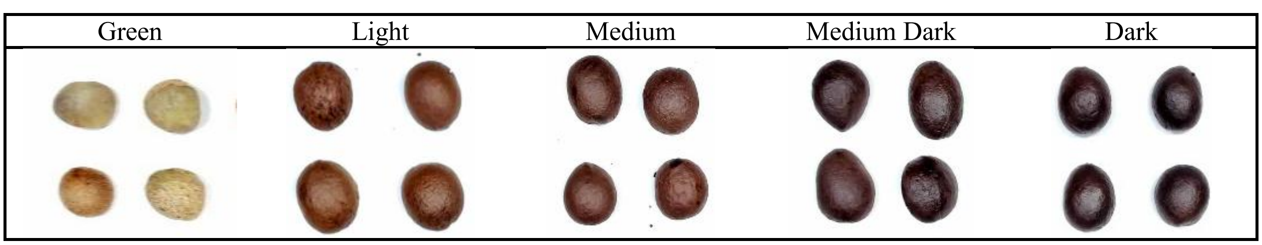

Figure 6. Label all coffee categories.

The graph shows two peak groups (bimodal distribution) in each coffee category. This bimodal distribution indicates variability in bean size, which may introduce intra-class variation and potentially reduce classification performance, particularly for adjacent roasting levels. The bimodal distribution implies that the objects are not uniform in size, with some being small and others large. Most green label have an area of around 5,000–10,000, while the largest area in other bean groups is around 25,000–30,000. The area of objects with the highest frequency in each roasted coffee category has a value of around 30,000–45,000. The majority of green have a perimeter value of around 600 with a peak of 1200. The four categories of roasted coffee are relatively compactly distributed in the range of 700–900, with almost uniform peaks. A small portion of roasted coffee is spread across a larger perimeter, with a range of 1200–1500.

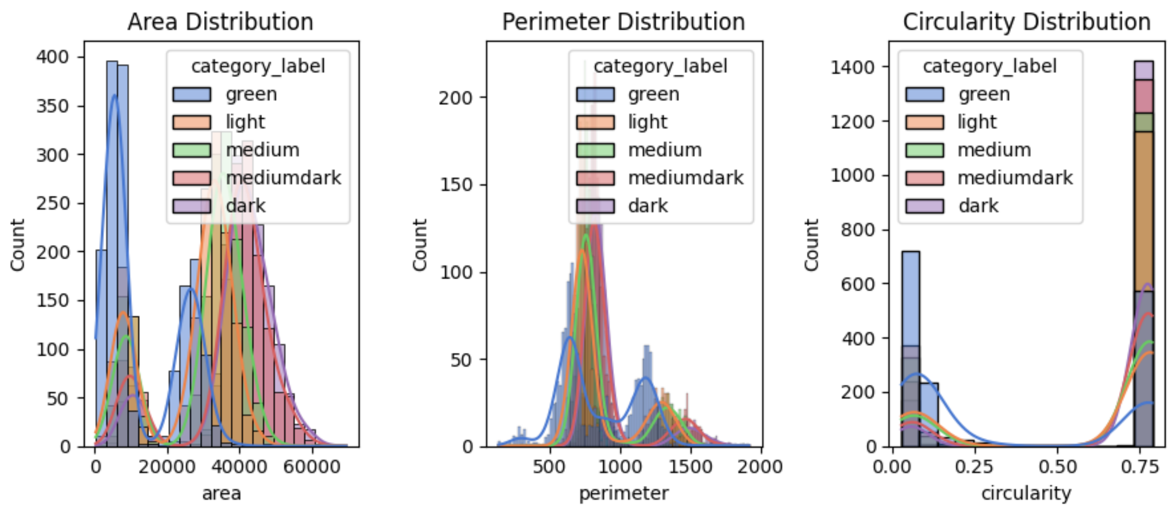

Figure 7. Feature shape histogram

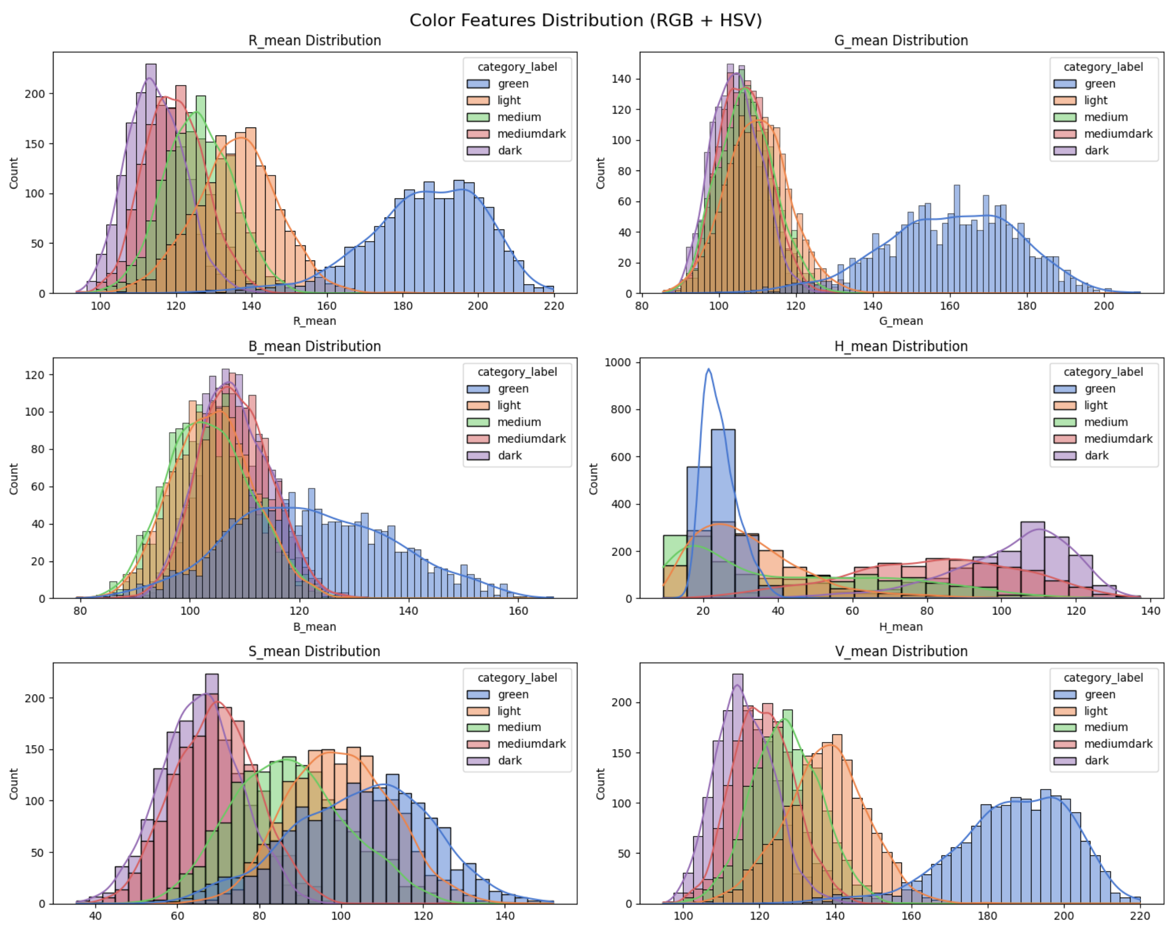

Figure 8. Feature color histogram

The majority of circularity in green and the four roasting categories have two relatively concentrated values. Concentration in low circularity values (0–0.2) indicates that the object is not round, while objects with high circularity values (0.7–0.8) indicate that the object's surface tends to be round. This occurs because heat generated during roasting causes structural expansion and surface cracking in the beans. Based on Figure 8, we can observe an increase in area, perimeter, and circularity values that it becomes more spherical and more homogeneous in shape. Roasting coffee beans at high temperatures can cause a nearly 80% volume expansion (Bustos-Vanegas *et al*., 2018). The volume expands in all directions, increasing the object's area and perimeter. These physical transformations justify the inclusion of shape features (area, perimeter, circularity) alongside color features to improve classification robustness.

From the graph, it can be seen that increasing roasting intensity decreases the *R*, *G* and *B* values. A consistent decrease in RGB intensity values was observed with increasing roasting degree, indicating progressive darkening due to Maillard reactions and caramelization. The difference in color features is most clearly seen in beans in the green category compared to other categories. On the other hand, the H-mean value has a different trend from other color features. The H-mean value shifts to the right in line with the type of roasting treatment. This shift in value indicates a change in the color of the coffee from green to light brown, then to brown and finally to dark brown, in line with the increasing darkness of the roasting degree. The higher the average value, the more the treatment tends towards dark. The shift in H-mean reflects hue transitions from green to brown tones, although its relationship with roasting intensity is less direct compared to intensity-based features (RGB and V).

In this study, accuracy was simulated across three data division ratios (70:30, 80:20 and 90:10) to determine which provided the best accuracy. The division of each amount of calibration data and validation data as shown in Tabel 1.

Table 1. Distribution of calibration and validation data

Dataset Partition	Calibration Data	Validation Data
70:30	5600	2400
80:20	6400	1600
90:10	7200	800

The performance of the model in accurately predicting objects is determined by its accuracy value. The accuracy value for each dataset division is obtained by using different k-neighbour values. Testing for the best *k* value starts from k1 to k30 and is displayed on the metric graph. Each *k* value provides its own error rate, where the lowest error rate at a certain *k* value at the elbow point is the *k* value that provides the highest accuracy value. Determining this *k* value has a significant effect on the accuracy value produced (Ardiyansyah & Oktafiani, 2024). The classification performance for the dataset division that achieved the highest accuracy is detailed in Table 2.

Table 2. Classification performance metrics for different dataset partitions

Dataset partition	Label	Value of *k*	Precision	Recall	F-1 Score	Accuracy
70:30	Green	30	1.00	0.99	1.00	82.04%
	Light		0.90	0.93	0.91	
	Medium		0.80	0.79	0.79	
	Medium Dark		0.66	0.64	0.65	
	Dark		0.74	0.76	0.75	
80:20	Green	22	1.00	1.00	1.00	81.81%
	Light		0.90	0.93	0.91	
	Medium		0.82	0.79	0.81	
	Medium Dark		0.65	0.61	0.63	
	Dark		0.72	0.76	0.74	
90:10	Green	16	1.00	0.99	1.00	83.00%
	Light		0.90	0.92	0.91	
	Medium		0.83	0.84	0.83	
	Medium Dark		0.68	0.63	0.66	
	Dark		0.73	0.77	0.75	

In the 90:10 data split, the best k value obtained to provide the highest accuracy is k = 16 (Figure 9). Lower k values tend to overfit the training data, while higher k values reduce sensitivity to class boundaries. The selected k = 16 provides a balance between bias and variance, resulting in optimal classification performance. The highest precision, recall, and F-1 scores are for the green label, with values of 0.99–1.00 across all evaluation types. The F-1 score trend in this split is the same as in the previous split. The first rank is occupied by green, followed by light (0.91), medium (0.83), dark (0.75), and finally medium dark (0.66). The precision and recall values have increased slightly compared to the previous data split. The overall classification accuracy in this data split is 83.00%. The dataset is limited to controlled lighting conditions and a specific acquisition setup, which may reduce generalization to real-world environments. In addition, the evaluation was conducted using a single random data split; therefore, the results may be sensitive to data partitioning. Future studies should incorporate cross-validation techniques to ensure model robustness and reliability.

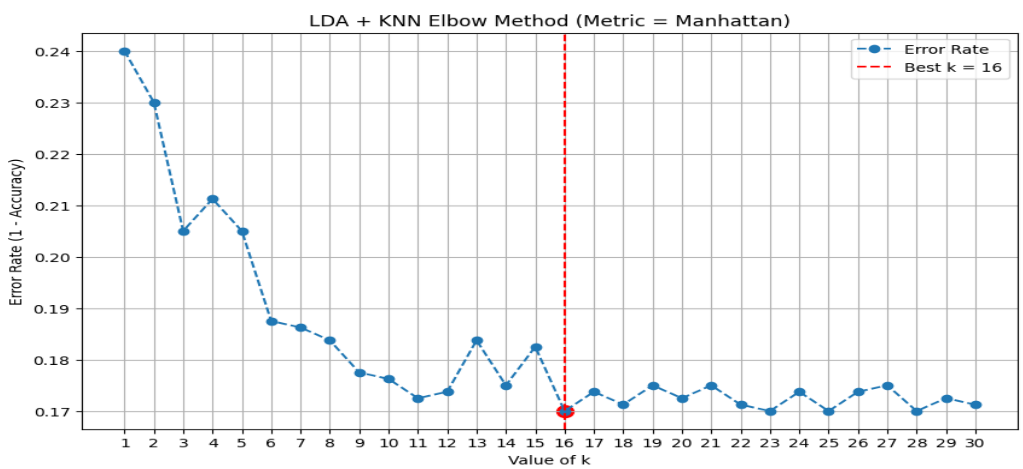

Figure 9. The k optimal for 90:10 data split

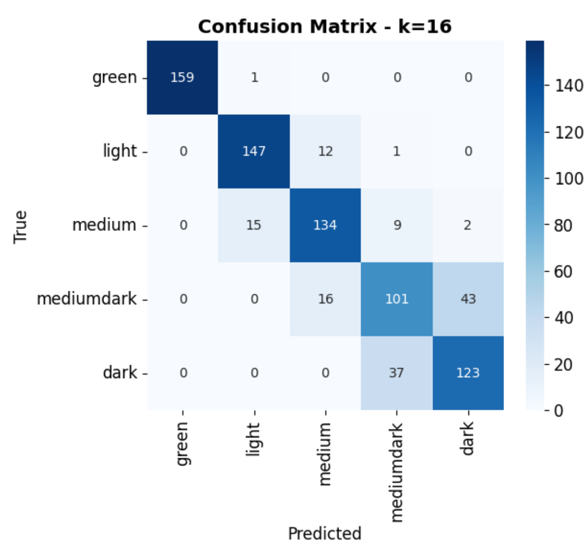

Figure 10. Confusion matrix for 90:10 data split

Of all the metric evaluations, green ranked highest, followed in order by light, medium, dark, and medium dark. Coffee labelled medium dark is roasted between medium and dark, so its color falls between the two labels. Therefore, the system struggles to correctly distinguish labels between closely adjacent color hues. Previous research also encountered low accuracy when classifying categories with colours that were close to each other (Wibawa *et al*., 2021). The accuracy obtained was 55% when detecting yellow roast coffee and 40% when detecting light roast. In fact, the same value was found when detecting light roast and medium roast.

4. CONCLUSIONS

The use of the KNN algorithm with color and shape parameters has successfully classified five categories of roasted coffee. This study demonstrates that integrating color and shape features with LDA-based dimensionality reduction improves the classification of Robusta coffee roasting levels. The best model achieved 83.00% accuracy using a 90:10 data split with k = 16. However, classification performance remains limited for intermediate roasting levels due to feature overlap. Future work should focus on improving feature representation and employing more advanced classification models to enhance discrimination between visually similar classes.

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AUTHOR CONTRIBUTION STATEMENT

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
DKTR	✓	✓	✓	✓					✓	✓	✓			
UA	✓									✓		✓		
SSM	✓									✓		✓		

C: Conceptualization; M: Methodology; So: Software; Va: Validation; Fo: Formal Analysis; I: Investigation; D: Data Curation; R: Resources; O: Writing - Original Draft; E: Writing - Review & Editing; Vi: Visualization; Su: Supervision; Fu: Funding Acquisition; P: Project Administration

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