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Coffee Beans Classification Using Convolutional Neural Networks Based On Extraction Value Analysis In Grayscale Color Space

Bagus Raffi Santoso [1]*, Christy Atika Sari [2], Eko Hari Rachmawanto [3]
[1,2,3]Department of Informatics Engineering, Faculty of Computer Science, University of Dian Nuswantoro, Semarang 50131
bagusraffi232@gmail.com [1], atika.sari@dsn.dinus.ac.id [2], eko.hari@dsn.dinus.ac.id [3]

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ABSTRACT

Coffee is a vital agricultural commodity, and precise classification of coffee beans is crucial for quality assessment and agricultural practices. In this study, we propose a methodology utilizing Convolutional Neural Networks (CNN) based on ResNet-101 architecture for coffee bean classification. The novelty of our approach lies in the integration of comprehensive feature extraction from grayscale coffee bean images, including mean, standard deviation, skewness, energy, entropy, and smoothness, with the transfer learning capabilities of CNN. Through this integration, we achieved exceptional classification performance, with the CNN model attaining accuracy, recall, precision, and F1-score metrics of 99.44% and 100% on the training data, and 100% on the testing data. These results underscore the robustness and generalization capability of our methodology in accurately classifying coffee bean types. While the dataset used in this study is experimental, the comprehensive feature extraction and the effectiveness of the CNN architecture suggest the potential for accurate classification of coffee bean types beyond the experimental data, provided the new data shares similar characteristics to the collected samples. For future research, we recommend exploring the integration of two transfer learning techniques within CNN architectures to further enhance coffee bean classification systems. Specifically, leveraging pre-trained CNN models as a foundation for feature extraction, while simultaneously fine-tuning specific layers to adapt to the nuances of coffee bean classification tasks, could offer improved model performance and scalability.

I. Introduction

Coffee is one of the most valuable agricultural commodities, playing a crucial role in generating foreign exchange revenue for many countries [1]. In Indonesia, coffee provides a livelihood for approximately 1.5 million coffee farmers [2], [3]. Besides its economic importance, coffee is renowned for its health benefits, such as alleviating headaches, easing respiration, and boosting stamina [4]. Globally, coffee has remained a popular beverage from past to present, with consumption increasing annually [5]. Indonesia ranks as the world's third-largest coffee producer in 2022/2023. The two primary types of coffee, Robusta and Arabica, each have distinct characteristics. Arabica coffee, with its lower caffeine content and higher acidity compared to Robusta, commands a higher market price [3], [6]. The beans of these two varieties also differ in shape. However, many farmers and coffee entrepreneurs, including coffee shop owners, struggle to accurately distinguish between these types. Sorting, a process crucial for separating Robusta and Arabica beans before they reach the market, is traditionally performed manually by visual inspection of a 100-gram sample (approximately 100-200 beans). This manual classification method is prone to errors due to human eye fatigue [7].

Based on these problems, the research objective of this study is to classify the two types of coffee beans, Robusta and Arabica, using Convolutional Neural Networks (CNN). CNN are advanced computational models inspired by the human brain's structure and function, making them particularly effective for image classification tasks. By extracting features from the beans based on grayscale color space analysis, neural networks can accurately distinguish between different classes of coffee beans. This method is especially suitable for this problem due to its ability to learn complex patterns and features in image data, ensuring high accuracy and consistency in classification.

Many researchers examine CNN to classify coffee beans based on shape, color and other patterns. Tamayo-Monsalve et al. [8] proposed a CNN method to clasify their coffee fruit based on multispectral image data. The study evaluated the performance of five popular CNN architectures for classifying cherry coffee fruits according to their ripening stage. Their study achieved a remarkable accuracy exceeding 98% when tested on 600 coffee fruits representing five different stages of ripening. The results demonstrated the efficacy of their approach in providing farmers with a highly accurate and efficient method for classifying coffee fruits. Putra et al. [9] proposed a comprehensive study aimed at identifying the types of coffee plants based on leaf image identification. Their study utilized a dataset comprising 19,980 images, which were divided into training and testing sets, consisting of 15,984 and 3,996 images, respectively. Their study meticulously considered hyperparameters, revealing that employing 100 epochs and a learning rate of 0.0001 yielded the highest accuracy. Evaluation was conducted using 10-fold cross-validation and ROC analysis. Notably, their CNN architecture achieved the highest accuracy of 97.67%, outperforming LeNet (97.20%), AlexNet (95.10%), ResNet-50 (72.35%), and GoogleNet (82.16%) in accurately identifying coffee plant types based on leaf images. Heryanto et al. [10] introduced a CNN-based model, utilizing Mask R-CNN, to recognize coffee bean defects. They used a dataset of 480 images categorized into black, broken, and hole classes, with 360 images for training and 120 for validation. The model achieved 93.3% accuracy for individual object testing and 75% for plural object testing, showing promise in automated defect recognition.

Based on the three researchers above, who explored CNN-based approaches for coffee classification, the novelty of this study lies in the utilization of a CNN architecture based on ResNet-101 for classification purposes. By leveraging transfer learning from ResNet-101, which incorporates a deeper network structure compared to ResNet-50, this study aims to enhance the classification accuracy and robustness for coffee type prediction. This approach presents a notable advancement in the field, offering potential improvements in accuracy and performance compared to previous studies. The comparison between ResNet-101 and other pre-trained models provides valuable insights into the effectiveness of deeper architectures for coffee classification tasks.

II. Method

The proposed method proposes two main phases: pre-processing and classification. In the pre-processing phase, the process initiates with data collection followed by conversion to grayscale, facilitating uniformity and simplification of the image data. Subsequently, feature extraction techniques are applied to capture relevant information from the grayscale images, focusing on extraction value analysis to discern distinguishing characteristics among coffee bean types. Transitioning to the classification phase, parameters are initialized, and the ResNet-101 layers are initialized as part of the transfer learning process. The model is then trained on the pre-processed data, leveraging the extracted features to facilitate learning and optimization. Model evaluation is conducted based on a confusion matrix, allowing for a comprehensive assessment of the model's performance across different classes. Flow of proposed method can be seen in Figure 1.

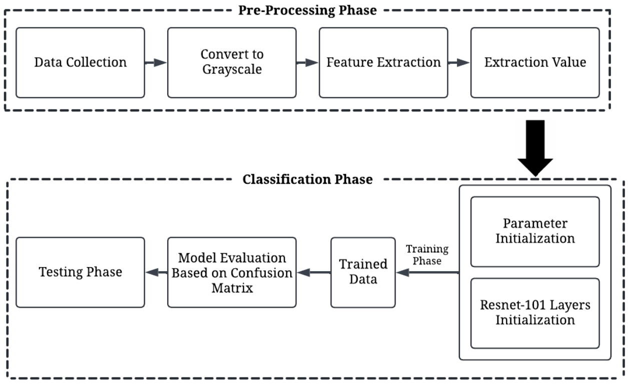


Figure 1. Proposed Methodology

A. Data Collections

In the data collection phase, the dataset comprises a total of 900 images, evenly distributed across three classes: Arabica, Liberica, and Robusta, with 300 samples per class. Each image has a resolution of $256 \times 256 \times 3$, representing RGB color space. To ensure a robust training process and reliable evaluation, the dataset is split into training and testing subsets using an 80:20 ratio. Specifically, 80% of the dataset (720 images) is allocated for training, while the remaining 20% (180 images) is reserved for testing.

The dataset includes sufficient variation in coffee beans to account for differences in regional origins, environmental conditions, and physical characteristics of the beans. This variability enhances the generalizability of the model and ensures it can accurately classify coffee beans across diverse contexts. Based on sample data can be seen in Figure 2.

(a) Arabica (b) Robusta (c) Liberica

Figure 2. Sample Dataset Each Class

B. Feature Extraction

In the feature extraction phase, several key features are derived from the grayscale images to effectively characterize the coffee beans [11], [12]. Each extracted feature from grayscale images contributes significantly to distinguishing different coffee bean types. The mean represents the average pixel intensity, providing an initial indication of the overall brightness of the coffee beans, which is particularly useful for distinguishing Arabica from Robusta [13]. The standard deviation measures the variation in pixel intensities, reflecting the texture's contrast, with higher values indicating coarser textures, as commonly observed in Robusta beans, and lower values indicating smoother textures, as seen in Arabica [13]. Additionally, entropy quantifies the randomness or complexity of the image texture. High entropy values suggest intricate and irregular patterns, aiding in identifying more complex textures, such as those of Arabica beans. Energy, on the other hand, reflects the uniformity of the texture, with higher energy values signifying a more homogeneous texture, which is characteristic of certain bean types. Skewness captures the asymmetry in the intensity distribution, highlighting unique visual patterns or contours in the coffee beans [14]. Finally, smoothness measures the relative smoothness of the bean surface, offering a metric for identifying differences in surface characteristics, such as the generally smoother surface of Liberica beans compared to Robusta [15]. Feature extraction equation can be seen in Eq (1) – (6).

$$Mean = \frac{1}{N}\sum_{i=1}^{N} xi \quad (1)$$

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(xi - Mean)^2} \quad (2)$$

$$Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{(xi - Mean)^2}{SD}\right) \quad (3)$$

$$Energy = \sum_{i=1}^{N} p(xi)^2 \quad (4)$$

$$Entropy = -\sum_{i=1}^{N} p(xi)\log(p(xi)) \quad (5)$$

$$Smoothness = 1 - \frac{1}{1 + SD^2} \quad (6)$$

C. CNN Layers and Parameter

In this phase, there are 2 steps namely train and fine-tune the ResNet-101 model, several parameters are carefully initialized to optimize performance [16]. The training process involves 16 epochs, allowing the model ample iterations to learn from the dataset. A learning rate (LR) of 0.0001 is selected to ensure gradual and stable weight updates during training. The batch size is set to 32, striking a balance between computational efficiency and model performance. The Adam optimizer is employed for its adaptive learning rate properties, which enhance the training process. Cross-entropy loss is used as the loss function, given its suitability for multi-class classification problems, effectively measuring the difference between the predicted and actual labels. These parameters collectively contribute to the robust training and fine-tuning of the ResNet-101 model for accurate coffee bean classification [17], [18].

After initializate parameter conducted above, the second step begins with an input layer for grayscale images (224x224), followed by an initial convolutional layer with 64 filters of size 7x7, batch normalization, ReLU activation, and max pooling. The network features four main residual blocks with bottleneck designs. The first block includes three convolutional layers (64, 64, and 256 filters) with identity shortcuts, repeated twice more. The second block increases the filters to 128, 128, and 512, with projection shortcuts for downsampling, repeated three more times. The third block, crucial for depth, uses 256, 256, and 1024 filters with projection shortcuts, repeated 22 times. The fourth block comprises 512, 512, and 2048 filters, with projection shortcuts, repeated twice more. The network concludes with global average pooling, a fully connected layer with 1000 units (modifiable for specific tasks), and a softmax output layer for class probabilities, tailored for three coffee bean classes: Arabica, Liberica, and Robusta.

D. Model Evaluation Based on Confusion Matrix

Model evaluation based on the confusion matrix provides a comprehensive assessment of the classification performance for coffee beans. The confusion matrix consists of four key metrics: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These metrics enable the calculation of important performance indicators such as accuracy, sensitivity (recall), specificity, precision, and F1 score. Accuracy measures the overall correctness of the model by accounting for all correctly classified instances (both TP and TN) relative to the total number of instances. Sensitivity/recall indicates the model's ability to correctly identify positive instances (specific coffee bean types), while specificity measures its ability to correctly identify negative instances [19], [20]. Precision assesses the correctness of positive predictions, and the F1 score harmonizes precision and recall into a single metric, balancing their contributions. Based on confusion matrix evaluation can be seen in Eq (7) – (10).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

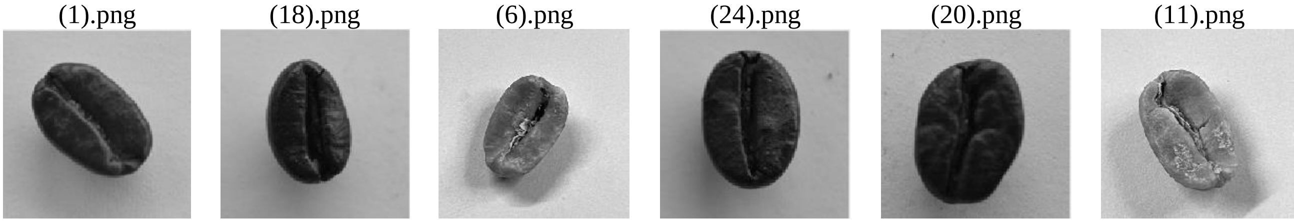
$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision \times Recall} \tag{10}$$

III. RESULTS AND ANALYSIS

In this work, MATLAB software is used to perform the pre-processing and classification steps of the introduced approach. In the pre-processing step, different operations like image enhancement, resizing, and feature extraction have been performed in order to prepare the data in an adequate format for analysis. Then, the classification is implemented via MATLAB's powerful computation tools to achieve a valid result. These functionalities together under one platform ensured smooth execution and enabled effective evaluation of the introduced methodology.

Process begins with preprocessing steps that included resizing the images and converting them to grayscale. Resizing the images ensured a consistent input size of 224x224 pixels, which is required for the ResNet-101 model. After resizing, the next step is converting the images to grayscale to reduce the computational complexity while retaining essential features for classification. The results from the preprocessing phase, which include resizing and grayscale conversion, can be seen in Figure 3. In this figure, the images have been standardized to a consistent size of 224x224 pixels and converted to grayscale, effectively reducing computational complexity while preserving essential features. These preprocessing steps have produced clean, uniform data that is ready for training, ensuring optimal performance and accuracy in the subsequent classification tasks. Figure 3 exemplifies the effectiveness of these preprocessing techniques in preparing the dataset for the ResNet-101 model.

(a) Arabica (1).png | (b) Robusta (18).png | (c) Liberica (6).png | (d) Arabica (24).png | (e) Robusta (20).png | (f) Liberica (11).png



(g) Arabica Processed | (h) Robusta Processed | (i) Liberica Processed | (j) Arabica Processed | (k) Robusta Processed | (l) Liberica Processed

Figure 3. Pre-Processed Dataset Each Class

The results of feature extraction obtained from the grayscale images in Figure 3 are presented in Table 1. This table showcases the extracted features, including MU, SD, skewness, energy, entropy, and smoothness, for each coffee bean sample. These features provide valuable insights into the textural and statistical properties of the coffee beans, facilitating their classification into distinct classes.

TABLE I
RESULTS OF PRE-PROCESSED EXTRACTION

Sample Testing	Mean	SD	Skewness	Energy	Entropy	Smoothness
Arabica (1).png	138.2023	58.2403	-2.667	0.015991	4.6455	0.96377
Robusta (18).png	140.2099	59.2935	-3.7161	0.017658	4.5736	0.965
Liberica (6).png	182.8461	47.8435	-2.3151	0.019261	4.5386	0.94724
Arabica (24).png	120.1561	57.997	-2.1214	0.014698	4.6723	0.96384
Robusta (20).png	117.8412	65.9333	-2.3663	0.012023	4.7223	0.97151
Liberica (11).png	184.2402	43.0186	-1.2107	0.014186	4.7282	0.93554

The analysis of the extracted features, as shown in Table 1, underscores their critical role in the classification process. Features such as the mean and standard deviation enable the model to capture variations in brightness and texture, which are fundamental for distinguishing between the coffee bean types. Entropy, with its ability to quantify randomness, plays a crucial role in identifying the more intricate textures of Arabica beans compared to the simpler textures of Robusta. Similarly, energy and smoothness contribute by highlighting uniformity and surface properties, respectively, enabling finer differentiation among the bean types. The skewness feature further supports the classification by identifying asymmetries in the pixel intensity distribution.

After got feature extraction values, the next step is training phase. Training phase was conducted using 80% of the data from the 300 sample images per class. This training process was executed on a high-performance computing system equipped with a Ryzen 7 7800X3D processor, 32GB RAM, 2TB SSD, and an RTX 4070 TI graphics card. Leveraging the advanced specifications, the training process exhibited remarkable efficiency, completing in a mere 52 seconds. MATLAB 2020a was utilized for the training, benefiting from its robust capabilities for deep learning tasks. The utilization of such powerful hardware and software resources not only expedited the training process but also ensured optimal utilization of computational resources, enabling rapid iteration and refinement of the ResNet-101 model for accurate coffee bean classification. Based on training process can be seen in Figure 4.

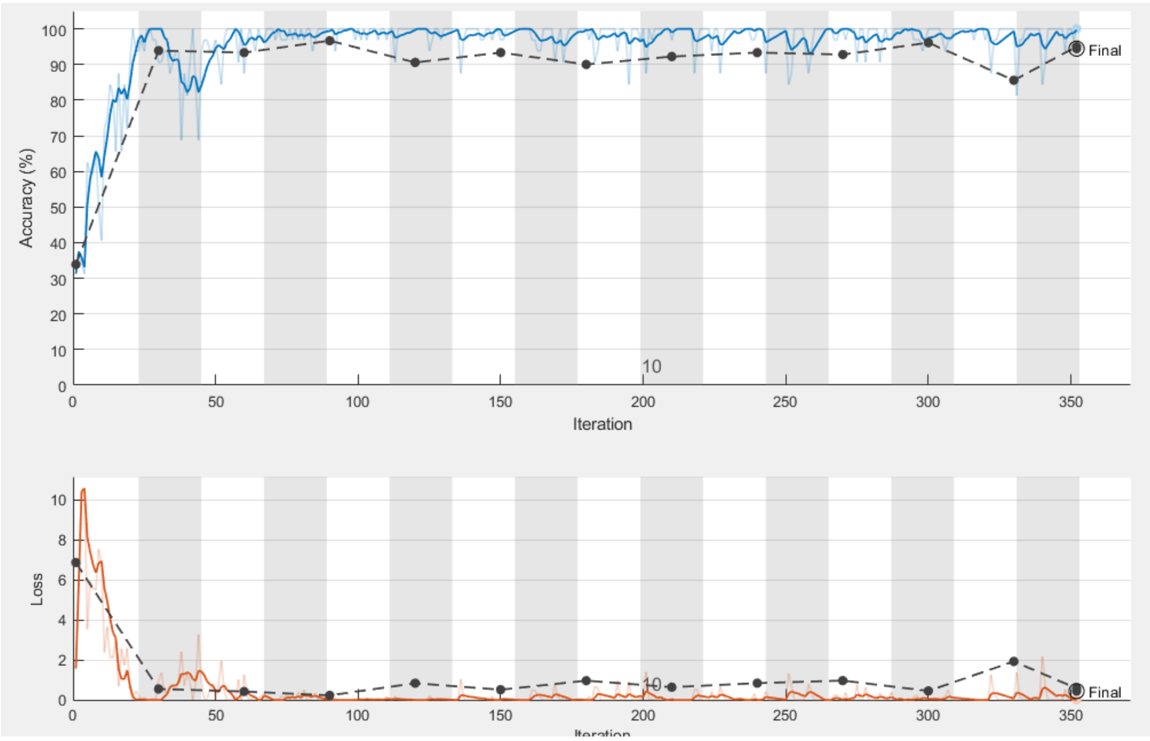


Figure 4. Model Training and Loss

The training progress results, depicted in the graph presented in Figure 4, culminated in the evaluation outcomes showcased in Table 2. The graph illustrates the iterative improvement of the model's performance metrics, such as accuracy, loss, and validation accuracy, over successive epochs during the training process. This graphical representation offers valuable insights into the convergence and refinement of the ResNet-101 model over time. Concurrently, Table 2 provides a detailed summary of the model's performance metrics, including accuracy, sensitivity/recall, specificity, precision, and F1 score, obtained after the completion of the training process. These evaluation metrics serve as benchmarks for assessing the model's effectiveness in accurately classifying the coffee bean samples into their respective classes, validating the efficacy of the training regimen and the suitability of the ResNet-101 architecture for the task at hand.

TABLE II
RESULTS OF CONFUSION MATRIX

Evaluation	Accuracy	Recall	Precision	F1-Score
80% Training Data	99.44%	100%	100%	100%
20% Testing Data	100%	100%	100%	100%

Table 2 presents the results of the confusion matrix evaluation for the ResNet-101 model trained on 80% of the dataset and tested on the remaining 20%. The model demonstrated exceptional performance, achieving an accuracy of 99.44% on the training data and 100% on the testing data. The achieved accuracy of 100% refers specifically to the evaluation conducted on the testing subset, which consists of 20% of the total dataset, amounting to approximately 180 data samples. This result indicates that the model successfully classified all testing data as true positives, meaning every sample in the testing set was correctly predicted by the model without any misclassifications. Such a performance demonstrates the model's ability to generalize effectively and accurately identify the distinct features of each coffee bean class—Arabica, Liberica, and Robusta—within the scope of this study.

In comparison to the related research studies by Tamayo-Monsalve et al. [8], Putra et al. [9], and Heryanto et al. [10], this research stands out with its innovative approach to coffee bean classification. While previous studies focused on classifying coffee fruit ripening stages, identifying coffee plant types, and recognizing coffee bean defects, respectively, this study introduces a comprehensive feature extraction process. The utilization of essential statistical features extracted from grayscale coffee bean images enables precise differentiation between Arabica, Robusta, and Liberica coffee beans. The robust performance of the proposed approach is evidenced by exceptional accuracy, recall, precision, and F1-score metrics obtained during both training and testing phases. Notably, achieving 99.44% accuracy on the training data and a perfect 100% accuracy on the testing data underscores the efficacy and generalization capability of the methodology employed. Moreover, the integration of Convolutional Neural Networks (CNNs) with ResNet-101 architecture further enhances the reliability and accuracy of coffee bean classification, promising significant advancements in coffee quality assessment and agricultural practices. Additionally, while Tamayo-Monsalve et al. [8] achieved over 98% accuracy in classifying coffee fruit ripening stages using CNNs with multispectral image data, Putra et al. [9] attained 97.67% accuracy in identifying coffee plant types through leaf image identification with meticulous hyperparameter tuning and 10-fold cross-validation. Heryanto et al. [10] introduced a Mask R-CNN-based model for coffee bean defect recognition, achieving 93.3% accuracy for individual object testing and 75% for plural object testing. Despite the successes of these studies, the comprehensive feature extraction and robust classification performance demonstrated in this research position it as a significant advancement in the field of coffee bean classification.

IV. CONCLUSION

Based on evaluation, the utilization of comprehensive feature extraction has yielded promising results, as exemplified by the statistical features extracted from grayscale coffee bean images, including mean, standard deviation, skewness, energy, entropy, and smoothness. These features have facilitated precise differentiation between Arabica, Robusta, and Liberica coffee beans. Additionally, the application of Convolutional Neural Networks (CNNs) based on ResNet-101 architecture has resulted in exceptional classification performance. The CNN model achieved remarkable accuracy, recall, precision, and F1-score metrics of 99.44% and 100% on the training data, and 100% on the testing data, showcasing its robustness and generalization capability in accurately classifying coffee bean types. These findings underscore the promising potential of advanced deep learning techniques, particularly when coupled with comprehensive feature extraction methods, for enhancing coffee quality assessment and agricultural practices.

For future research endeavors, integrating both comprehensive feature extraction methods and transfer learning techniques within CNN presents a promising avenue for advancing coffee bean classification methodologies. By combining the strengths of feature extraction in capturing intricate textural and statistical characteristics of coffee beans with the transfer learning capabilities of CNN, researchers can potentially enhance the accuracy and efficiency of coffee bean classification systems. Leveraging pre-trained CNN models, such as ResNet-101, as a basis for feature extraction, while fine-tuning specific layers to adapt to the nuances of coffee bean classification tasks, could lead to improved model performance and generalization across diverse datasets.

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