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DEVELOPMENT OF ANDROID APPLICATION FOR COFFEE ROAST LEVEL CLASSIFICATION USING CNN MOBILENETV3 BASED ON DIGITAL IMAGE ANALYSIS

Pengembangan Aplikasi Android Untuk Klasifikasi Tingkat Sangrai Kopi Menggunakan CNN MobileNetV3 Berbasis Citra Digital

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ABSTRACT

Coffee is one of Indonesia's key commodities with high economic value in both domestic and international markets. Roasting is a crucial stage in coffee processing, as it directly influences the final taste and aroma. However, until now, the roasting level has been determined visually and subjectively, making it prone to human error. This study aimed to develop an automatic classification system for coffee roasting levels using a Convolutional Neural Network (CNN) approach integrated into an Android application. The CNN model was built using the MobileNetV3 architecture and applied with a transfer learning method on Google Colab. The dataset consisted of 1,600 coffee images with three roasting levels: light, medium, and dark. The trained model was then converted into TensorFlow Lite (TFLite) format for integration into an Android application called RoastScan. This app features automatic classification through the camera or gallery and provides real-time predictions with confidence levels. The evaluation results show that the model has a classification accuracy of 97% on the test data, with high precision, recall, and F1-score across all classes. Further testing via the application showed that the best accuracy reached 93.55%. These findings suggest that integrating CNN with mobile applications has the potential to be a practical, efficient, and accurate solution for determining coffee roasting degrees, as well as supporting the standardization of coffee product quality at both industrial and MSME levels.

Keywords: Classification, Coffee Roast Level, CNN, Android, MobileNetV3

ABSTRAK

Kopi merupakan salah satu komoditas unggulan Indonesia yang memiliki nilai ekonomi tinggi, baik di pasar domestik maupun internasional. Salah satu tahap krusial dalam pengolahan kopi adalah proses sangrai (roasting), yang secara langsung memengaruhi cita rasa dan aroma akhir. Namun, hingga kini, penentuan tingkat kematangan sangrai masih banyak dilakukan secara visual dan subyektif, sehingga rentan terhadap kesalahan manusia. Penelitian ini bertujuan untuk mengembangkan sistem klasifikasi otomatis tingkat kematangan sangrai kopi menggunakan pendekatan Convolutional Neural Network (CNN) yang diintegrasikan ke dalam aplikasi Android. Model CNN dibangun menggunakan arsitektur MobileNetV3 dan diterapkan dengan metode transfer learning di Google Colab. Dataset yang digunakan terdiri dari 1.600 citra kopi dengan tiga kelas sangrai: light, medium, dan dark. Model yang telah dilatih kemudian dikonversi ke dalam format TensorFlow Lite (TFLite) agar dapat diintegrasikan ke aplikasi Android bernama Roasting Level App. Aplikasi ini memiliki fitur klasifikasi otomatis melalui kamera atau galeri, dan menyajikan hasil prediksi beserta confidence level secara real-time. Hasil *evaluasi menunjukkan bahwa model memiliki akurasi klasifikasi sebesar 97% pada data uji, dengan nilai precision, recall, dan F1-score yang tinggi pada seluruh kelas. Pengujian lebih lanjut melalui aplikasi menunjukkan akurasi terbaik mencapai 93,55%. Temuan ini menunjukkan bahwa integrasi CNN dengan aplikasi mobile berpotensi menjadi solusi praktis, efisien, dan akurat dalam menentukan derajat sangrai kopi, serta mendukung standarisasi mutu produk kopi di tingkat industri maupun UMKM.*

Kata Kunci: klasifikasi, derajat sangrai kopi, CNN, Android, MobileNetV3

INTRODUCTION

Coffee is one of Indonesia's leading commodities with high economic value (Putra et al., 2020). Indonesia ranks as the fourth-largest coffee producer in the world, after Brazil, Vietnam, and Colombia. Approximately 67% of the total domestic coffee production is exported, and the remaining 33% is consumed domestically. Indonesian coffee is exported to five continents, with primary destinations including the United States, Egypt, Germany, and Malaysia (BPS, 2024).

Based on a survey by LPEM UI in 1989, the domestic coffee consumption rate was 500 g/capita/year. Currently, coffee industry stakeholders estimate that consumption in Indonesia has reached 800 g/capita/year. Consequently, within a 34-year period, coffee consumption has increased by 300 g/capita/year (Widodo et al., 2022). Despite this growth, the Indonesian coffee industry still faces obstacles due to poor coffee quality, which affects the final production output (Indonesia Investments, 2024). The primary causes include improper handling during fermentation, cleaning, sorting, drying, and roasting (Batubara et al., 2019). Therefore, the implementation of appropriate cultivation and processing technologies is key to producing high-quality coffee (Pakaya et al., 2026).

To produce a flavorful cup of coffee, the beans must undergo a process called roasting (Radi et al., 2020). The roasting process plays a crucial role in determining the flavor and aroma of coffee (Nasir et al., 2019). Roasting levels are generally categorized as light, medium, and dark. However, determining these levels is often done subjectively by roasters, which can lead to inconsistencies in the quality of the coffee produced (Pakaya et al., 2024).

Computer vision is a technology developed to determine coffee roast levels (Hendriyana dan Maulana, 2021). Computer vision functions similarly to human vision, identifying objects in the form of images, which are then extracted for information and classified. One approach within computer vision is the use of Artificial Neural Networks inspired by the human brain, which have been further developed into Deep Learning (Lecun et al., 2015). Currently, the most significant Deep Learning method is the Convolutional Neural Network (CNN) (Azizah et al., 2018).

Alongside technological advancements, particularly in the field of Artificial Intelligence, the Convolutional Neural Network (CNN) method has proven effective in image processing for object classification. CNN can extract visual features from images with high accuracy, making them suitable for classifying coffee roast levels. Previous studies have developed Android-based applications that utilize CNN to classify roasting levels with promising accuracy results (Muresan and Oltean, 2018).

Numerous studies have been conducted to determine coffee roast levels using digital image processing. Nugraha and Wiguna (2018) first developed a system to identify coffee roast levels using artificial neural networks, achieving an accuracy of 76.7%. Additionally, Putra et al. (2020) developed a system to determine coffee roast levels using RGB detection and minimum distance classification, resulting in an accuracy of 89.63%. Furthermore, Prastyaningsih and Kusrini (2021) achieved an accuracy of 97.67% in identifying roast levels through color feature extraction using an image retrieval system. However, the fundamental weaknesses of these models are their heavy computational requirements and errors in object detection.

Michael et al. (2020) developed an Android application for coffee roast level

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classification using CNN with LeNet5, AlexNet, and MiniVGGNet architectures. The results showed that the combination of LeNet5 with the ADAM optimization function produced the highest accuracy (98 %). Enriquez et al. (2024) compared various CNN models for coffee bean classification and found that DenseNet, MobileNet, and ResNet152 models provided the best accuracy. However, the resulting model outputs were large and computationally intensive for use in Android-based applications.

Based on this background, this study aims to develop an Android application that can automatically classify coffee roast levels using CNN. This application is expected to assist roasters in determining roast levels objectively and consistently, while also helping consumers choose coffee according to their preferences. The results of this study are expected to support the standardization of coffee quality and provide a tangible contribution to the coffee industry in the digital age.

MATERIALS AND METHODS

Requirement Analysis

To conduct this research, a laptop was used for system development, while an Android smartphone was used for data collection and the implementation of the developed coffee roast level determination system. In addition, a photo box equipped with two LEDs was used for image acquisition. The application for determining coffee roast levels was designed using Android Studio Narwhal 2025.1.1 Patch 2 with the Kotlin programming language. Other applications utilized in this research included Google Colaboratory as the operating medium, Google Chrome as the platform to run Google Colaboratory, and Firebase for database storage.

The materials used in this study consisted of images of roasted coffee beans. The images used for the model training process were sourced from the "Cap Kadal Roaster" roasting house and were labeled by experts into three classifications: light, medium, and dark. The collected image dataset was subsequently divided into three parts: training, validation, and testing sets. Figure 1 illustrates how a group of coffee beans is photographed individually to obtain single images for the training dataset.

Figure 1. Coffee bean samples were manually sorted and labeled for dataset collection.

Data Collection and Preparation

Figure 2 shows the image acquisition process using a smartphone in a photo box. The acquired image data were then separated into different folders based on the roasting level. The dataset was also partitioned for training and testing purposes. The total number of images in the dataset was 1,600, divided into 1,200 for training and 400 for testing.

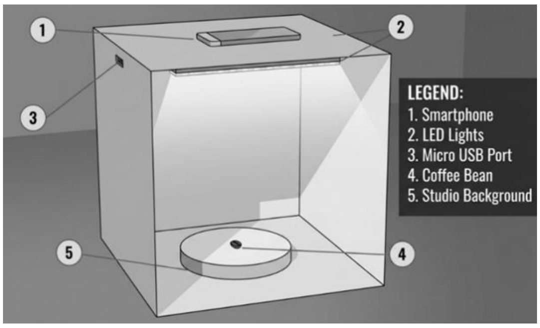

Figure 2. The dataset image acquisition process was performed using a photo box (20 × 20 × 20 cm) with two LED lights.

Data Pre-Processing

Figure 3 presents a flowchart of the dataset pre-processing aimed at enhancing the image quality and facilitating object identification by the system. The pre-processing of the training data included resizing, normalization, and augmentation, whereas only resizing and normalization were applied to the testing data. The primary objective was to prepare the data for effective utilization by the CNN model.

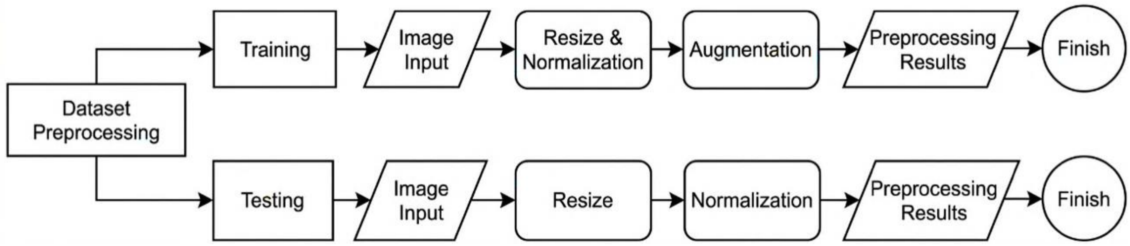

Figure 3. Dataset preprocessing flowchart.

Model Architecture and Training

Machine learning (ML) model programming was conducted in Google Colab using the TensorFlow (TF) 2.0 library. Transfer Learning will be employed to construct the model. Transfer learning is the utilization of an existing machine learning model to solve a similar problem, and is typically used to avoid building a model from scratch (Rabano et al., 2018). MobileNet was selected as the model for transfer learning. This model is designed to achieve high accuracy with a small number of parameters, allowing it to be implemented at low computational costs on mobile platforms. The latest version, MobileNetV3, was used in this study.

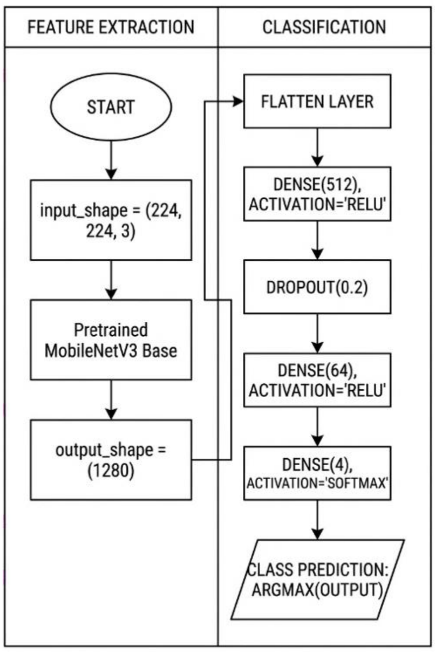

Figure 4. CNN model design.

Application Development and Testing

Figure 5 illustrates the system design of the Android application. The images to be classified were uploaded to Firebase and then predicted using the prebuilt CNN model. The prediction results were then evaluated; if unsuccessful, modifications were made to the application or model. If successful, an analysis of the prediction results was performed to determine the coffee roast level.

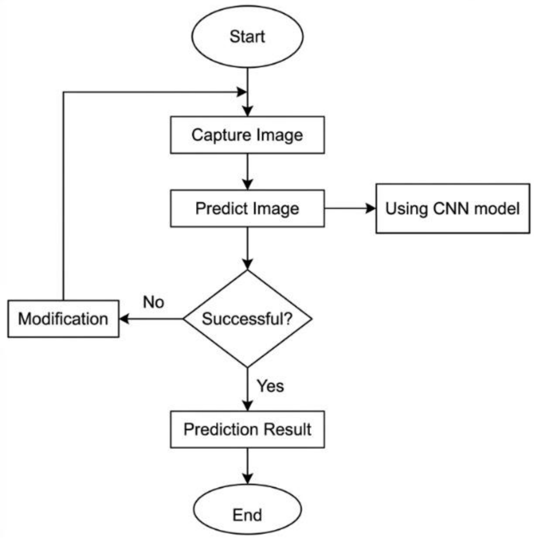

Figure 5. Android application system design diagram.

The designed application features two distinct functions: capturing images directly or selecting them from the smartphone gallery, followed by predicting the classification of the acquired image. Once the application was successfully developed, feature testing was conducted. General testing of Android applications is categorized into two types: unit testing and instrumentation testing. Unit testing examines the business rules within the application system, with JUnit being the most commonly used framework (Mario et al., 2017). Instrumentation testing focuses on the application's UI and can be automated using the Espresso library developed by Google as part of Android Studio (Sergio et al., 2020).

The application was tested using a coffee image dataset in JPG format.

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Validation tests were performed using a confusion matrix and evaluation system to assess the model's performance. The confusion matrix was used to compare the prediction results with the actual conditions, identifying true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Detailed information on the confusion matrix is presented in Table 1.

Table 1. Confusion Matrix

Prediction	Actual	
	Positive	Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Negative (FN)	True Negative (TN)

RESULTS AND DISCUSSION

Dataset Characteristics

The dataset used in this study consisted of 1,600 images, with 400 images for each roast level (Table 2). The roast levels used were green, light, medium, and dark. Each category was organized into separate folders and divided into two datasets: training and testing.

Data Visualization

Figure 6 illustrates the visualization results of the stored dataset for each category, featuring four different images randomly selected from the total pool of images. All displayed images were highly clear, with distinguishable differences that facilitated the object recognition process.

Model Training Evaluation

The evaluation results of the model training using 1,200 datasets for each maturity level demonstrated the CNN model's performance in classifying four coffee roast levels: dark, green, light, and medium (Figure 6). Of the 300 images per class, the model successfully classified the dark and green classes exceptionally well, with 298 and 299 correct predictions, respectively. The light class achieved 295 correct predictions. The medium class showed the lowest performance, with 273 images being correctly classified.

Table 2. Annotation File Snippet (CSV)

Class_index	*Filepaths*	*Labels*	*Categories*	*Datasets*
0	*green*	*dataset/train/green/gr...*	*green*	*train*
1	*green*	*dataset/train/green/gr...*	*green*	*train*
2	*green*	*dataset/train/green/gr...*	*green*	*train*
3	*green*	*dataset/train/green/gr...*	*green*	*train*
4	*green*	*dataset/train/green/gr...*	*green*	*train*
...	...	...	...	...
1595	*light*	*dataset/test/light/lig...*	*light*	*test*
1596	*light*	*dataset/test/light/lig...*	*light*	*test*
1597	*light*	*dataset/test/light/lig...*	*light*	*test*
1598	*light*	*dataset/test/light/lig...*	*light*	*test*
1599	*light*	*dataset/test/light/lig...*	*light*	*test*

1600 rows × 4 columns

Table 3 presents the Classification Report of the CNN model for coffee roast level classification. It can be concluded that the model exhibits excellent overall performance. All evaluation metrics showed high values, reflecting the model's capability to accurately classify images across all four classes. For the dark class, the model obtained precision, recall, and F1-score of 0.99, indicating that nearly all predictions for this class were correct, with minimal errors. The green class achieved a perfect score (1.00) across all three metrics, indicating that the model could identify this category without error. The light class obtained a precision of 0.92 and a recall of 0.98, indicating that the model is frequently accurate in identifying this class, despite a few mispredictions. The medium class had the lowest recall (0.91), which is consistent with the confusion matrix results, as some images from this class were misclassified. Overall, the model achieved an accuracy of 0.97, with both the macro and weighted averages consistently reaching 0.97, demonstrating a stable and balanced performance across all classes.

Figure 6. Data visualization results

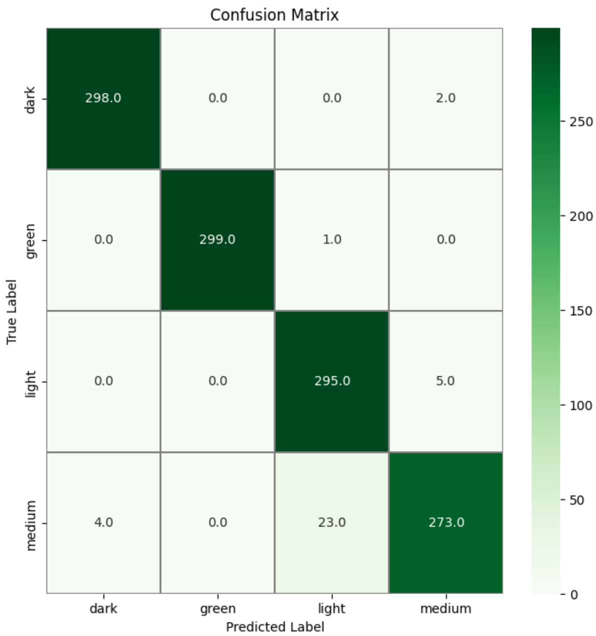

Figure 7. CNN model Confusion Matrix

Table 3. Classification report Confusion Matrix model CNN

Category	Precision	Recall	F1-Score	Support
Dark	0.99	0.99	0.99	300
Green	1.00	1.00	1.00	300
Light	0.92	0.98	0.95	300
Medium	0.97	0.91	0.98	300
Accuracy			0.97	1200
Macro Avg	0.97	0.97	0.97	1200
Weighted Avg	0.97	0.97	0.97	1200

Application Implementation

The Android application was developed using the Android Studio IDE and Kotlin programming language (JVM version 1.8), integrating various dependencies such as Retrofit, Firebase, and Glide. Before system construction, the model was saved in the TFLite format to enable implementation within the application system. The following are the implemented interface details (Figure 8):

1. The Start Screen Figure 8a shows the classification application interface. The developed Android application features a single page or activity that houses all the utilized functions. This application is called “RoastScan.”
2. Open Directory Screen Figure 8b shows the open directory screen. Two buttons are provided for image input: "Take Picture" to capture a photo directly and "Launch Gallery" to select an image from storage.
3. The Full Activity Screen Figure 8c illustrates the user interface (UI) workflow of the Roasting Level App, designed to classify coffee roast levels using the CNN model. The application includes a "History" submenu to store the classification results, which contains a record of all predictions along with the analyzed images. This simple and intuitive interface allows various users including farmers, MSMEs (Micro, Small, and Medium Enterprises), and coffee roasters—to use the application efficiently to improve the quality consistency of their roasted products

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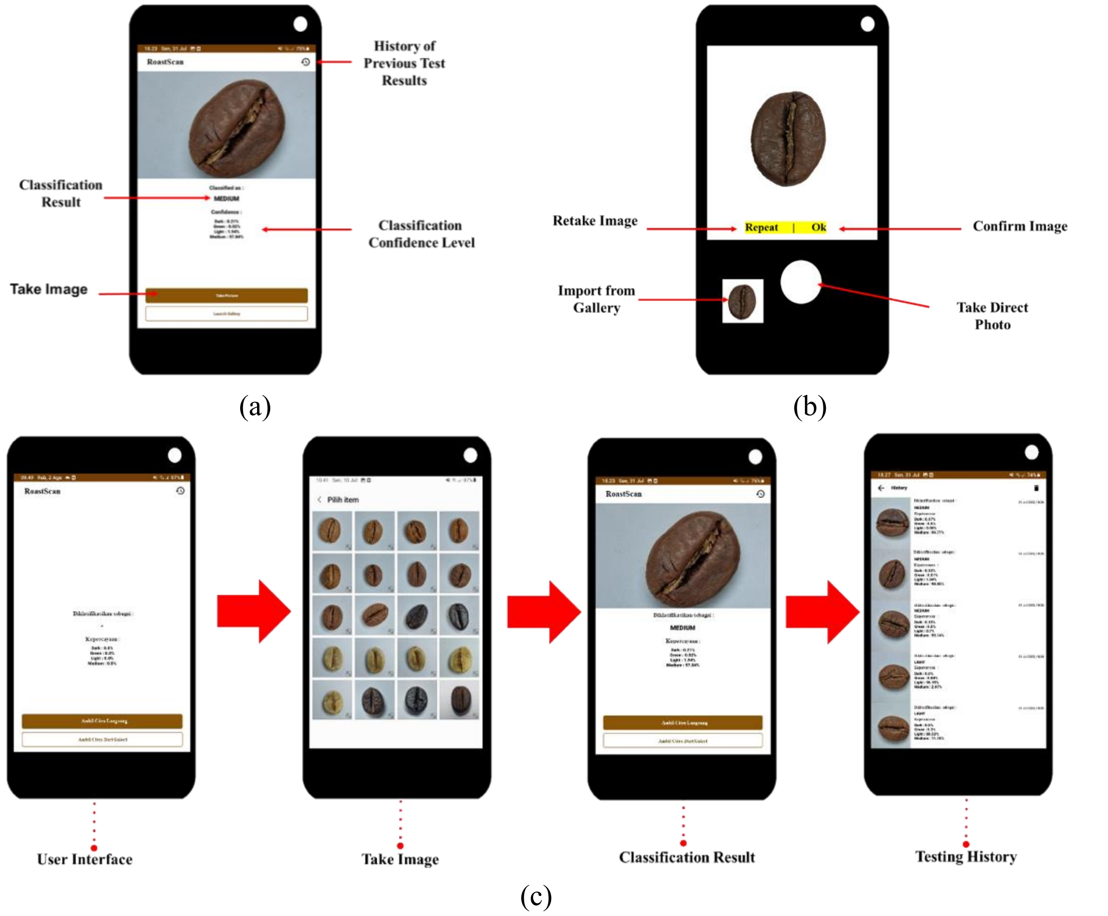


Figure 8. The interface of the developed Android application. *Start screen (a), open directory screen (b), and full activity screen (c).*

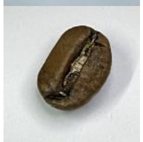
Application Testing

To gain a deeper understanding of the application's performance, experiments were conducted using two test datasets. These two types of Test Data are distinguished by their acquisition methods: Test Data 1 (roasted coffee images from "Cap Kadal Roaster") and Test Data 2 (roasted coffee images from the Kaggle website, uploaded by Gerry under the title "Coffee Bean Dataset Resized (224x224)"). The total number of images was limited to 240, with 120 images in each test set. Each category contained 30 images in total. The differences between the two test datasets are listed in Table 4.

Based on the test results, the system successfully classified all images for the dark, green, and light roast levels in Test Data 1. For the medium roast category, 26 images were correctly classified, whereas four were misidentified. In Test Data 2, the system successfully classified all the images in the green category. However, for the dark roast level, only 19 images were correctly classified, with 11 errors. For the light roast level, 10 images were correctly classified, and 20 were incorrect. The lowest performance occurred at the medium roast level, with only seven correct classifications and 23 misidentifications. Significant misidentifications were still observed in the dark, light, and medium categories of Dataset 2 (Figure 9).

Subsequently, the classification test results were analyzed to calculate the precision, recall, accuracy, and F1-score of the application. Table 5 presents an analysis of the classification results.

Table 4. Differences between Test Data 1 and Test Data 2

Test data	Dark	Green	Light	Medium
1				
2				

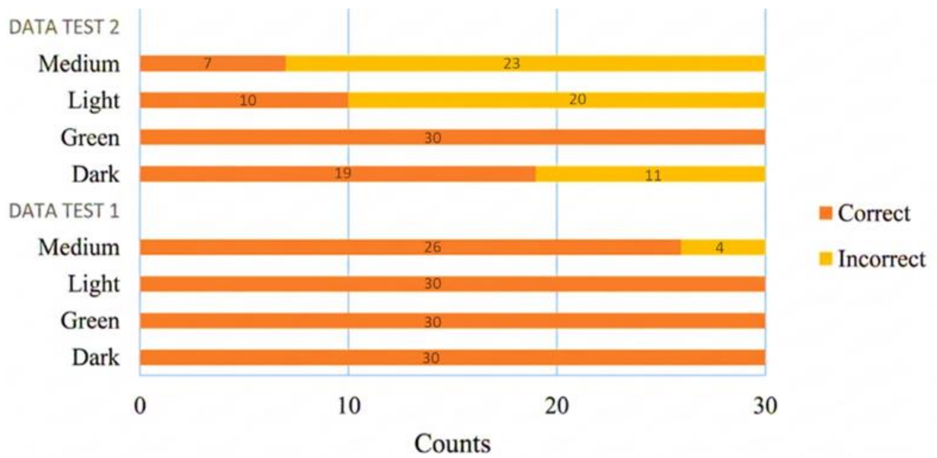


Figure 9. Application testing results

Table 5. Test data analysis results

Category	TP	TN	FP	FN	Precision (%)	Recall (%)	Accuracy (%)	F1-Score
Test Data 1								
Dark	30	0	0	0	100,00	100,00		1,00
Green	30	0	0	0	100,00	100,00	93,55	1,00
Light	30	0	4	0	88,24	100,00		0,94
Medium	26	0	0	4	100,00	86,67		0,93
Average					97,06	96,67	93,55	0,97
Test Data 2								
Dark	19	0	0	11	100,00	63,33		0,78
Green	30	0	0	0	100,00	100,00	54,10	1,00
Light	10	0	1	20	90,91	33,33		0,49
Medium	7	0	23	1	23,33	87,50		0,37
Average					78,56	71,04	54,10	0,66

Note: TP = True Positive; TN = True Negative; FP = False Positive; FN = False Negative; F1-Score, harmonic mean of precision and recall.

Based on the test results, Test Data 1 achieved high performance, with an accuracy of 93.55%, average precision of 97.06%, recall of 96.67%, and an F1-score of 0.97. This indicates that the CNN-MobileNet model effectively classified coffee roasting levels when the test images had characteristics similar to the training data, supporting

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previous findings on the reliability of CNN-based coffee roast classification (Pakaya et al., 2024; Marzuki et al., 2025).

However, Test Data 2 showed lower accuracy, reaching only 54.10%, mainly because of misclassification in the dark, light, and medium classes. This result suggests that the generalization ability of the model is still limited when applied to images with different color characteristics, lighting conditions, camera settings, backgrounds, coffee origins, and roasting profiles. Because the roast level is closely related to bean color, differences in color distribution between the training and testing data can significantly affect the classification performance (Alamri et al., 2023; Motta et al., 2025).

Therefore, although the developed Android-based application performed well on Test Data 1, further improvement is needed. Expanding the training dataset with more variations in roasting conditions, coffee varieties, lighting, cameras, and image-acquisition settings is recommended. Controlled photometric augmentation, such as brightness, contrast, and color variation, may also improve model robustness, provided that it does not alter the actual roast class identity (Shorten & Khoshgoftaar, 2019; Xu et al., 2023). Overall, CNN-MobileNet is promising for coffee roast classification; however, broader and more diverse training data are required to improve generalization.

CONCLUSSIONS

In this study, a coffee roast level classification system was successfully developed using a Convolutional Neural Network (CNN) model with a MobileNetV3 architecture. The model was trained using a coffee bean image dataset covering four roast levels and demonstrated high performance, with an accuracy of 97%. Subsequently, the model was converted into the TensorFlow Lite (TFLite) format and implemented in an Android application called the Roasting Level App. This application allows users to classify coffee directly via the camera or gallery, providing informative results and confidence levels. The testing results indicated a peak accuracy of 93.55% on the internal test data, whereas the performance on the external data required further improvement through the addition of dataset variations. The application is practical, efficient, and user-friendly, with the potential to assist MSMEs and coffee industry stakeholders in enhancing product quality and consistency. Overall, this system serves as an innovative solution for the digitalization of coffee processing.

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