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Classification of Arabica Coffee Bean Images from Roasting Using the Convolutional Neural Network Resnet50v2 Method with Transfer Learning

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Abstract

The roasting level of Arabica coffee beans plays a crucial role in determining product quality, sensory characteristics, and market value, yet its assessment in practice is often subjective and inconsistent due to manual visual inspection. This study aims to develop a roasting level classification model for Arabica coffee beans using the ResNet50V2 Convolutional Neural Network (CNN) architecture based on transfer learning. The dataset used consists of Arabica coffee bean images with four roasting levels (Green, Light, Medium, and Dark) obtained from a publicly available dataset. Three training scenarios were applied using data split ratios of 60:40, 70:30, and 80:20, with each model trained for 10 epochs under identical experimental settings. Model performance was evaluated using accuracy and F1-score. The best results were achieved in the 80:20 scenario, with a validation accuracy of 98.75% and an F1-score of 0.9875. These results indicate that increasing the proportion of training data significantly improves model stability and classification accuracy. This study contributes by providing an objective, image-based approach for roasting level classification and demonstrating the effect of training data proportion on CNN performance to support coffee quality control.

Keywords

Classification, Coffee Bean Image, Convolutional Neural Network, ResNet50V2, Roasting, Transfer Learning.

1. Introduction

Arabica coffee holds strategic value in the global coffee industry chain due to its high sensory quality and economic value (Vegro & de Almeida, 2020). The roasting level is a key factor that determines the color, aroma, texture, and final flavor character of a coffee product. However, in practice, determining the roasting level in small to medium-sized industries still relies on manual visual inspection by roasters. This traditional approach is susceptible to perceptual bias, fatigue, lighting variations, and differences in experience between assessors, resulting in quite high quality variability (Amrine et al., 2019; Santos et al., 2020). To ensure quality consistency, an automated image-based system is needed that is able to identify the roasting level objectively and can be replicated.

Advances in computer vision and deep learning, particularly through Convolutional Neural Networks (CNNs), have provided models capable of extracting visual features automatically and accurately (Dhillon & Verma, 2020; Liu et al., 2021; Zhao et al., 2024). CNNs have been proven effective in assessing the visual quality of agricultural commodities such as coffee leaves, coffee cherries, and determining roasting levels (Esgario et al., 2020; Bazame et al., 2021; Anto et al., 2024; Lavanya et al., 2025). The ResNet architecture introduced by He et al. (2016) introduces a residual learning mechanism to mitigate the vanishing gradient problem, while the ResNet50V2 variant offers better training stability through a pre-activation scheme, making it suitable for fine-featured images such as the surface of coffee beans.

In addition, transfer learning allows the use of pre-trained model weights such as ImageNet, so that model performance remains optimal even though the dataset is relatively limited, a common condition in agro-industry research (Motta et al., 2024). Various recent studies have shown that deep learning approaches are able to distinguish roasting levels with high accuracy (Chang et al., 2021; Marzuki et al., 2025; Rivas et al., 2025). However, previous studies generally used a single training–testing data configuration, so they have not provided a comprehensive picture of the model's sensitivity to variations in the amount of training data, the size of the test data, or the duration of training. This comparison is important because variations in training–testing data proportions directly affect model generalization, robustness, and reliability, particularly when using limited datasets.

This study used three training scenarios with data splits of 60:40, 70:30, and 80:20. All scenarios were trained using the same number of epochs, namely 10 epochs, so that performance evaluation was conducted under constant training conditions. This approach was designed to specifically assess how variations in training data proportions affect the accuracy and stability of the ResNet50V2 CNN model in classifying Arabica coffee bean roast levels. The roasting level of Arabica coffee beans plays a crucial role in determining product quality and sensory characteristics, yet its assessment in practice remains subjective due to manual visual inspection. Although previous studies have demonstrated the effectiveness of Convolutional Neural Networks for coffee roasting classification, most of them rely on a single training–testing data configuration, leaving the impact of training data proportion on model stability and performance insufficiently explored. To address this gap, this study aims to develop a roasting level classification model using the ResNet50V2 architecture with a transfer learning approach and to systematically evaluate the effect of different training–testing data splits on model performance.

2. Methods

This study uses an experimental approach with three training-test data split scenarios (60:40, 70:30, and 80:20). The main model is a CNN with the ResNet50V2 architecture as the feature extractor, and a custom classification layer on top is shown in Figure 1. All experiments were run with the same architectural configuration and training parameters, allowing for fair performance comparisons between scenarios.

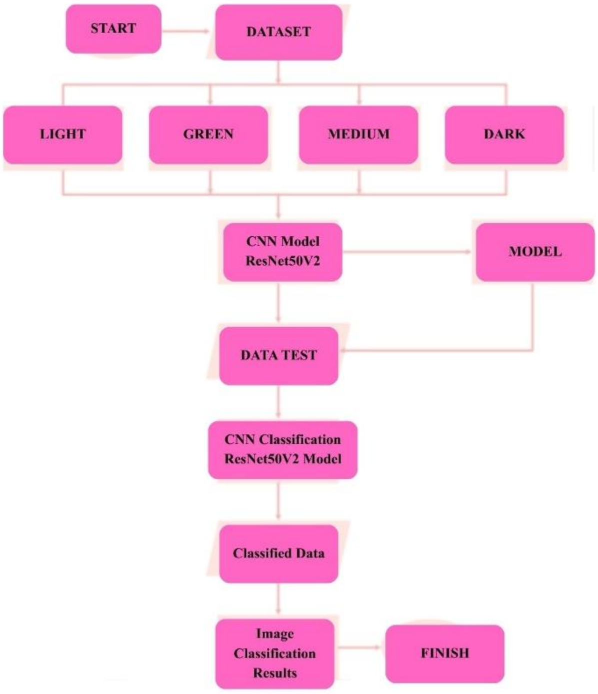


Figure 1. Research Design Diagram

The dataset used in this study comes from the Coffee Bean Dataset – Resized 224×224, publicly provided by Gerry (2025) through the Kaggle platform. The dataset contains images of Arabica coffee beans in four roasting levels: Green, Light, Medium, and Dark. All images have undergone an initial resizing process by the dataset provider so that they have uniform dimensions of 224×224 pixels, making them compatible with various transfer learning-based CNN architectures. For experimental purposes, the dataset was then reprocessed and adapted to the ResNet50V2 architecture. All images were resized to 64×64 pixels, normalized to the [0,1] range, and grouped according to training requirements. At this stage, the dataset was divided into three training–testing proportions, namely 60:40, 70:30, and 80:20. Each data proportion was trained using 10 epochs, resulting in three training scenarios. The experimental workflow consists of image preprocessing and augmentation, dataset splitting into training and testing sets, feature extraction using a pre-trained ResNet50V2 backbone, model training under three data split scenarios, and performance evaluation using accuracy, F1-score, and confusion matrix analysis

Preprocessing and augmentation have been shown to improve CNN performance in coffee roasting classification (Kurniawan et al., 2022; Anto et al., 2024; Ardian et al., 2024; Saleh & As'ad, 2025). The ResNet50V2 architecture was selected due to its reported training stability on fine-featured images, while transfer learning is widely applied in agricultural product classification (He et al., 2016; Esgario et al., 2020; Bazame et al., 2021; Sagita et al., 2024). In this study, all images were resized to 64×64 pixels with RGB channels and normalized to the [0.1] range. Data augmentation techniques, including rotation, flipping, zooming, and brightness adjustment, were applied to the training set to increase data diversity and reduce overfitting, thereby improving model stability and generalization.

This study employs the ResNet50V2 architecture with pre-trained ImageNet weights for transfer learning. To enhance training stability on a limited dataset, the ResNet50V2 backbone is frozen and used as a feature extractor. Input images of 64×64 pixels with RGB channels are rescaled to the [0.1] range and processed through the backbone, followed by a Global Average Pooling layer to reduce feature dimensionality. A Dense Softmax layer with four neurons is then applied to classify the roasting levels into Green, Light, Medium, and Dark. This configuration follows standard transfer learning practices, where pre-trained networks serve as robust feature extractors and task-specific layers learn domain-relevant characteristics (Bazame et al., 2021).

The Adam optimizer was selected for its adaptive and efficient weight-updating mechanism, particularly suitable for deep architectures such as ResNet50V2. By combining momentum and RMSProp, Adam stabilizes gradients and accelerates convergence, making it effective for small to medium-sized image datasets (Ha et al., 2016; Kingma & Ba, 2017; Barve et al., 2025). Categorical cross-entropy was chosen as the loss function due to the multiclass nature of the task (Green, Light, Medium, and Dark). This loss function effectively measures the probabilistic difference between predicted and actual class distributions, enabling better discrimination among visually similar roasting levels. As the standard loss for softmax-based multiclass classification, it has demonstrated strong performance in agro-industry and food image analysis studies (Bazame et al., 2021; Rivas et al., 2025). Together, the Adam optimizer and categorical cross-entropy provide a stable and widely adopted framework for CNN-based Arabica coffee roasting classification.

Model performance evaluation is performed using several metrics that provide a comprehensive overview of the network's classification capabilities. The primary metric used is test data accuracy, which measures the proportion of correct predictions across all test samples. Furthermore, this study uses macro and weighted F1-scores to measure the balance between precision and recall for each class. The macro F1-score treats each class equally regardless of the number of samples, making it suitable for evaluating model performance on multiclass classification tasks. Meanwhile, the weighted F1-score provides an assessment based on the proportion of samples in each class, making it more representative of the actual distribution in the dataset.

For a more in-depth analysis, this study also generated a 4×4 confusion matrix to identify model error patterns in each class, including misclassification between visually similar roasting levels. The final stage of the evaluation was completed with a per-class error analysis to highlight which classes were most susceptible to prediction errors and what visual factors could potentially affect their performance. The use of the macro F1-score as the main indicator is based on its ability to provide a more balanced assessment of the performance of each class in a relatively balanced multi-class dataset (Abdula et al., 2024).

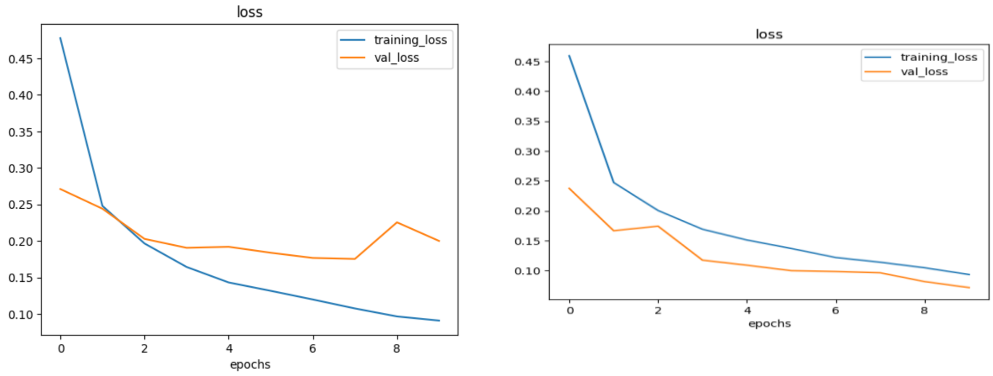
3. Results and Discussion

3.1. Model Performance in Roasting Level Classification

The experimental results demonstrate that the ResNet50V2-based CNN with a transfer learning approach is able to classify Arabica coffee roasting levels with high accuracy and stable convergence across all scenarios. This finding is consistent with previous studies that reported the effectiveness of CNN-based models for coffee roasting and quality assessment. Earlier works by Sarino et al. (2019) and Kurniawan et al. (2022) showed that image-based neural networks are capable of distinguishing roasting levels using color-related features, although their approaches relied on simpler architectures or fewer roasting classes.

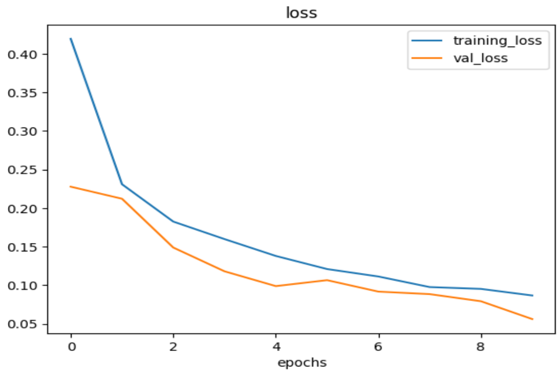
Compared to conventional RGB-based or shallow CNN methods, the use of a deeper architecture, such as ResNet50V2, allows the model to capture more complex visual patterns related to color gradients, texture, and surface characteristics of coffee beans. Similar advantages of deep CNN architectures have been reported in agricultural image classification studies, including coffee quality and roasting analysis (Amrine et al., 2019; Santos et al., 2020; Hassan, 2024). The high accuracy obtained in this study confirms that deep residual networks are well-suited for roasting level classification, particularly when combined with a transfer learning strategy (Pratondo et al., 2023; Razavi et al., 2024).

In the 60:40 scenario, the graph shows a consistent and stable decrease in training loss from the first to the tenth epoch. The training loss starts at a relatively high value (around 0.42) and gradually decreases to near 0.09. This trend indicates that the model is able to learn the visual patterns of the roasting level well as the number of epochs increases. Meanwhile, the validation loss also decreases from around 0.22 to around 0.06, although the decrease is slightly more fluctuating than the training loss. The small difference between the training and validation loss indicates that the model is not experiencing significant overfitting, but it remains sensitive to variations in the validation data due to the smaller amount of training data compared to the other two scenarios.



(a) Training Loss 80:20

(b) Training Loss 70:30



(c) Training Loss 60:40

Figure 2. Training Loss Graph

Based on Figure 2, the 70:30 scenario shows a more stable pattern of loss reduction than the 60:40 scenario. The training loss drops sharply from around 0.46 to a value near 0.10 by the end of training. The validation loss also experiences a strong decrease, from around 0.24 in the first epoch to around 0.07 in the tenth epoch. The pattern of both curves shows a narrowing gap between the training loss and validation loss, indicating that the model is becoming more stable and generalizing better to the test data. There is no significant spike in the validation loss, thus concluding that the 70% training data configuration provides the model with a richer learning space and reduces the risk of overfitting.

In the 80:20 scenario, the graph shows the best performance among the three scenarios. The training loss decreases very steadily from around 0.48 to nearly 0.09 at the end of the epoch, indicating optimal training. However, unlike the previous two scenarios, the validation loss shows slight fluctuations after the sixth epoch, where the validation loss value increases temporarily before decreasing again. This may be due to a combination of the high variation in the validation data and the model's ability to learn patterns from the larger dataset. Despite this slight variation in the validation loss, the model still achieves a very low final value (around 0.11–0.13), indicating continued good generalization performance. Overall, this trend confirms that using 80% training data proportion provides more stable training results, although validation may experience small fluctuations due to the relatively narrower distribution of test data.

3.2. Effect of Training–Testing Data Split on Model Performance

The comparative evaluation across different training–testing data splits reveals that increasing the proportion of training data leads to a consistent improvement in model performance. The 80:20 split achieved the highest accuracy and lowest loss, outperforming the 60:40 and 70:30 configurations. This result aligns with prior findings in coffee image analysis, where larger training datasets enable CNN models to learn more representative features and reduce classification errors (Vanegas et al., 2023; Halim & Riftiarrasyid, 2025).

Previous studies on CNN and ResNet architectures have emphasized that deep residual networks require sufficient training data to fully exploit their representational capacity (He et al., 2016). In addition, transfer learning studies in the coffee domain report that although pre-trained weights accelerate convergence, the final performance remains highly dependent on the amount of task-specific training data available (Anto et al., 2024; Motta et al., 2024). The superior performance of the 80:20 split in this study supports these observations and confirms that an optimal balance between training and testing data is critical for achieving stable and reliable classification results. The findings of this study are in agreement with recent systematic reviews highlighting that CNN-based models combined with transfer learning represent the current state-of-the-art approach for coffee quality and roasting level classification (et al., 2025).

Figure 3. Best Scenario Graphics

Figure 3 shows the best accuracy comparison graph for three data splits, which displays the dynamics of validation accuracy changes across three ResNet50V2 CNN training scenarios: 60:40, 70:30, and 80:20 splits over ten epochs. The graph shows that the 80:20 scenario consistently produces the highest accuracy across almost all epochs compared to the other two scenarios. In the first epoch, the three scenarios are at different initial accuracy ranges: 60:40 remains at 0.895, while 70:30 and 80:20 show higher initial performance with values of 0.902 and 0.925, respectively. As the number of epochs increases, all three curves show an increasing trend, but the speed and stability of this improvement differ significantly.

Table 1. Three Scenario Performance

Epoch	60:40 Accuracy	60:40 Loss	70:30 Accuracy	70:30 Loss	80:20 Accuracy	80:20 Loss
1	0.8953	0.2711	0.9023	0.2374	0.9250	0.2278
2	0.9125	0.2442	0.9480	0.1667	0.9250	0.2122
3	0.9125	0.2029	0.9397	0.1743	0.9469	0.1489
4	0.9234	0.1906	0.9543	0.1175	0.9500	0.1181
5	0.9297	0.1920	0.9667	0.1091	0.9688	0.0989
6	0.9359	0.1839	0.9667	0.0999	0.9563	0.1066
7	0.9359	0.1768	0.9709	0.0985	0.9563	0.0918
8	0.9375	0.1754	0.9709	0.0964	0.9625	0.0885
9	0.9266	0.2255	0.9667	0.0817	0.9781	0.0793
10	0.9312	0.2001	0.9771	0.0717	0.9875	0.0562

Based on Table 1, the 60:40 scenario exhibits slower accuracy gains and tends to plateau after the fifth epoch, with accuracy values fluctuating between 0.926 and 0.938. This curve illustrates the model's limitations in achieving optimal generalization due to the relatively small portion of training data. In contrast, the 70:30 scenario exhibits a more aggressive accuracy increase in the early epochs, reaching 0.948 in the second epoch and continuing to increase until stabilizing in the range of 0.967–0.978 in epochs 6 to 10. This curve appears smoother and exhibits a strong convergence pattern, indicating that a larger proportion of training data has a direct impact on the quality of model learning.

The 80:20 scenario, which has the largest portion of training data, produces the best and most stable performance. Validation accuracy increases consistently from the first epoch until it reaches its peak at around 0.987 in the tenth epoch. This curve demonstrates the model's ability to recognize visual patterns of roasting levels very well from the initial stage, then maintain a smooth upward trend until convergence.

The stable performance demonstrated in the final epoch, without any significant drop or fluctuation, indicates that the model did not experience overfitting despite the larger training data set.

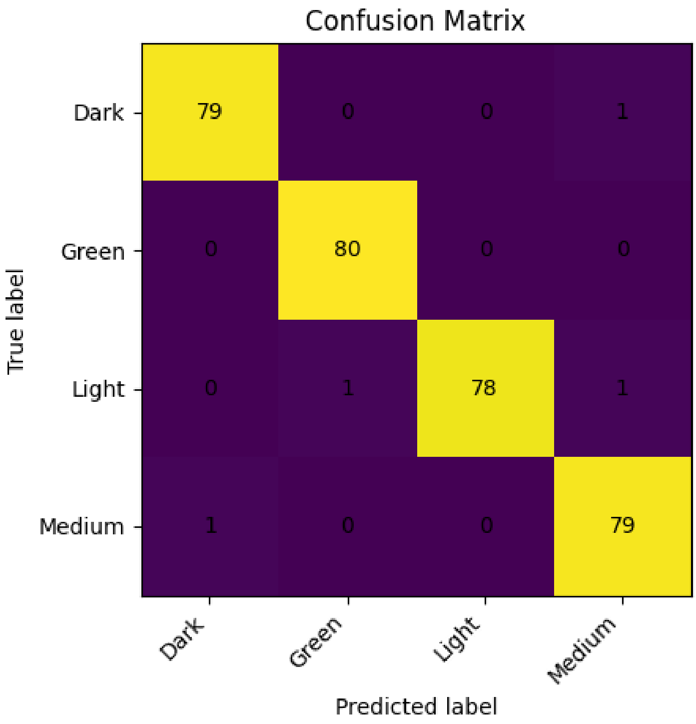


Figure 4. Confusion Matrix 80:20

Figure 4 shows that this graph illustrates that the greater the proportion of training data used, the higher the model's performance and stability. The 80:20 scenario achieved the best results and consistently became the optimal configuration for the classification of Arabica coffee roast levels. Meanwhile, the 70:30 scenario still showed strong and stable performance, while the 60:40 scenario, despite improving, still had the lowest accuracy level of the three. This trend underscores the importance of adequate training data availability in optimizing the performance of deep learning models in the image classification domain.

The results show that the 80:20 training–testing split achieves the best performance compared to the 60:40 and 70:30 scenarios, as indicated by higher accuracy and lower loss values. This finding is consistent with prior studies in coffee and agricultural image classification, which report that increasing the proportion of training data significantly improves CNN generalization capability (Amrine et al., 2019; Bazame et al., 2021; Putra et al., 2022). In contrast, studies using smaller training ratios often report higher variability and reduced stability in classification results (Santos et al., 2020; Esgario et al., 2020).

Specifically, Bazame et al. (2021) and Rivas et al. (2025) demonstrated that CNN-based coffee quality classification benefits from larger training sets, as the model is better able to learn subtle visual features such as color gradients and surface texture variations. Similar to their findings, the superior performance of the 80:20 split in this study suggests that a larger training set enables the ResNet50V2 model to extract more representative roasting-related features, while reducing misclassification between visually similar classes such as Light and Medium roasts.

Moreover, Motta et al. (2024) emphasized that transfer learning models applied to agro-industry datasets are particularly sensitive to training data proportion due to the limited size of domain-specific datasets. This observation explains why the 80:20 configuration in this study yields lower loss values and more stable convergence compared to the other splits. Therefore, in agreement with previous research, this study confirms that optimizing the training–testing data ratio is a critical factor in achieving robust and reliable CNN-based roasting level classification.

4. Conclusion

This study demonstrates that the ResNet50V2 Convolutional Neural Network architecture with a transfer learning approach can accurately and consistently classify Arabica coffee roast levels. Evaluation of three data split scenarios 60:40, 70:30, and 80:20 over ten epochs shows a consistent pattern of performance improvement as the training data portion increases. The 60:40 scenario demonstrates the model's basic ability to recognize visual differences between roast levels, but its performance remains limited due to the relatively small amount of training data. The 70:30 scenario provides significant improvement, with stronger accuracy, stability, and a more consistent reduction in loss, indicating more mature feature representation.

The 80:20 scenario emerged as the best configuration, with validation accuracy reaching 98.75% at the 10th epoch and a very stable learning trend with no indication of overfitting. These results indicate that the model has gained a deep visual understanding of the color, texture, and roast intensity characteristics of each roast class. This study confirms that the proportion of training data has a crucial role in optimizing the performance of deep learning models for food image classification, and an 80:20 configuration with sufficient training epochs can be recommended as an optimal standard for the implementation of an automated roasting level assessment system in the coffee industry. Nevertheless, this study is limited by the use of a single dataset and a fixed network architecture. Future research should explore larger and more diverse datasets, evaluate additional deep learning architectures, and investigate fine-tuning strategies to further improve model generalization and real-world applicability.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest.

Ethical Approval and Originality Statement

Ethical approval was obtained for this study. The manuscript represents original work and has not been previously published, nor is it under consideration by another journal.

Data Disclosure Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.