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# Classification of single origin Indonesian coffee beans using convolutional neural network

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**ABSTRACT**

This research aims to develop a coffee bean type detection model using convolutional neural networks (CNN), leveraging a dataset of 14,525 images from 116 types of Indonesian coffee beans. Pre-processing steps including resizing, rescaling, and augmentation were applied to improve the dataset quality. The dataset was split into training, validation, and testing sets with proportions of 80%, 10%, and 10%, respectively. Two model development approaches were used: transfer learning with Inception V3 in two scenarios and a model built from scratch. The transfer learning Inception V3 model in scenario 1 achieved the best performance, with a test accuracy of 0.87 and optimal evaluation metrics across precision, recall, and F1-score. This model was fine-tuned using pretrained weights, allowing it to adapt effectively to the coffee bean dataset. The results highlight that transfer learning, especially with Inception V3, provides a robust method for classifying coffee beans, offering potential applications in the coffee industry for improving classification efficiency and accuracy. The study demonstrates how deep learning can enhance the objectivity and precision of coffee bean classification, contributing to greater consistency in product sorting and quality assessment.

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## 1. INTRODUCTION

Indonesia, as the fourth-largest coffee producer in the world, was capable of producing 711.3 thousand tons of coffee beans annually before 2020 [1]. Coffee plays a vital role as a plantation commodity, contributing significantly to the national economy through export opportunities and a strong domestic market [2]. These opportunities are bolstered by Indonesia's steadily increasing coffee production each year, from 2020 to 2022. In 2022 alone, coffee production rose by 1.1% from the previous year, reaching 794.8 thousand tons [3]. Some of Indonesia's renowned coffee bean varieties include Arabica, Robusta, Liberica, Excelsa, and the famous *Kopi Luwak*. Coffee varieties are often influenced by the region or province of production, leading to more specific types of coffee. Additionally, dried coffee beans possess varying quality characteristics depending on their processing [4]. With this wealth of coffee types, classifying coffee beans by variety and quality is crucial for both entrepreneurs and farmers.

Currently, many coffee entrepreneurs and farmers still manually classify coffee beans by type and quality through workers or expert evaluators (cupper). This classification is based on visual inspection or sensory tests, which are subjective [5]. This subjectivity leads to inconsistencies in coffee bean classification. On the other hand, accurate classification is essential as it affects the productivity of the coffee beans, both in terms of flavor and quality, aligning with diverse consumer demands [6], [7]. Therefore, developing a classification method that can evaluate the characteristics of coffee bean types and quality more effectively and efficiently is necessary. Such a method must also be objective to ensure greater accuracy and consistency, addressing the shortcomings of manual classification, which is prone to high subjectivity.

In this regard, artificial intelligence (AI) technologies, such as machine learning and fuzzy logic, can be utilized to enhance the efficiency of coffee bean classification, as demonstrated in studies by Livio and Hodhod [8] and Santos *et al*. [9]. AI is used to improve both the accuracy and financial and time efficiency in identifying coffee bean types and quality. Machine learning methods such as artificial neural networks (ANN) [10], k-nearest neighbor (KNN) [11], and support vector machine (SVM) [12], [13] have been applied in coffee bean classification with high accuracy. However, the complex data processing required in coffee bean classification makes machine learning less suitable in some cases. One aspect of machine learning that can address this issue is deep learning. Deep learning can accommodate various variables involved in coffee classification, such as coffee bean type, roast level, geographical origin, and processing methods.

Deep learning is a branch of AI that uses neural networks consisting of many layers capable of recognizing complex patterns in data. Additionally, deep learning can automatically extract important features from complex, high-dimensional data. Therefore, it is well-suited for coffee classification processes involving intricate patterns, such as aroma, taste, color, size, shape, and texture characteristics of coffee beans. Deep learning includes several algorithmic methods that have proven accurate in coffee classification, such as multilayer perceptron (MLP), principal component analysis (PCA), ANN, and convolutional neural networks (CNN) [14]–[16]. Among these methods, CNN is the most frequently used for classification, especially when the process involves image data, as CNN offers high accuracy and superior performance in image classification [17].

However, in reality, the use of AI methods for coffee bean classification in Indonesia is still rare, resulting in suboptimal efficiency. This study seeks to address this gap, which is partly due to the limited amount of previous research on AI-based coffee classification in Indonesia. So far, a few studies in Indonesia have been conducted, such as Nasution and Andayani's [18] study on roasting level classification using image processing and ANN, powder coffee classification using ANN, and Suhandi and Yulia's [19] study on Arabica coffee powder classification using ultraviolet-visible (UV-Vis) spectroscopy technology.

This research applies CNN in the classification of Indonesian coffee bean types. Implementing CNN can improve production efficiency and enhance the value of Indonesian coffee commodities by reducing the time and costs associated with the sorting process. Moreover, this research can assist coffee producers in processing data related to coffee bean types and quality from various sources, leading to more accurate and better classification outcomes.

This study also contributes a novel dataset comprising 14,525 images from 116 single-origin Indonesian coffee bean types, which, to our knowledge, represents the most extensive dataset of its kind. The images were collected under standardized lighting and imaging conditions, ensuring consistency while capturing the wide morphological and color variations inherent to Indonesia's diverse coffee regions. Beyond supporting this study, the dataset offers substantial potential as a benchmark for future coffee classification research, facilitating cross-comparison of deep learning models and advancing the development of more generalized AI systems for agricultural product recognition.

## 2. LITERATURE REVIEW

The classification process for coffee beans can be carried out by observing the color, shape, size, taste, and aroma characteristics of the beans after the drying process [20], [21]. However, this process requires precision and consistency, which presents challenges when performed manually by workers. As a result, various supporting methods have been developed to automate the coffee bean classification process, one of which is the use of AI through deep learning methods. Deep learning is a branch of machine learning capable of solving highly complex problems by mimicking the way the human brain works. Components of deep learning include input, convolution, pooling, fully connected (dense) layers, and activation functions, depending on the network used [22]. Deep learning makes predictions by learning from input data to generate the desired output, identifying the correct item or action [23]. In this study, the data consists of images of coffee beans, which are used to produce output in the form of the correct type and quality classification of the beans.

Deep learning has been widely used in various classification processes, especially in the agricultural field [24]. Identifying and classifying parts of plants to ensure the expected quality has been a focus of many previous studies. In a study by Nasir *et al*. [25], a CNN model used to detect diseases in fruits based on color and shape characteristics achieved high detection accuracy. Beyond fruit disease detection, CNN models have also been applied to classify fruit types with an accuracy rate of 93% [1]. Early disease identification in plants through leaf analysis has also been conducted using CNN and image recognition techniques to achieve more accurate and efficient detection [26]. Moreover, deep learning has been used to identify seeds, such as in the study by Jumarlis *et al*. [27], where KNN was used to detect defects in coffee beans. Thus, deep learning is emerging as a promising tool for the inspection and classification of food quality and safety in the agricultural sector [28].

One of the most commonly used deep learning algorithms for classification and identification processes is CNN. CNN specializes in pattern recognition and uses connected layers of pooling and convolution to transform an input image into a series of feature maps, which are then classified by fully connected layers based on the image's features [29]. This mechanism allows CNN to excel in image recognition processes, effectively extracting color and shape features from images [30]. CNN is relatively easy to train and develop, depending on the breadth and depth of the dataset used during model training, and can accurately predict image properties [31]. However, to achieve high accuracy, CNN requires large datasets of image samples during the training phase [32]. The importance of pre-training to achieve high accuracy has been demonstrated by Unal *et al*. [33], who employed four CNN models to detect coffee beans, all of which achieved high accuracy after pre-training.

Given its advantages, CNN has been widely developed and implemented in coffee bean classification processes. Previous research has demonstrated the high accuracy of CNN in classification tasks, including those involving type, quality, and defect detection. Buonocore *et al*. [34] used CNN to automatically classify mixed Arabica and Robusta coffee beans, distinguishing them based on shape, color, and size from captured images, with highly accurate results.

Wang *et al*. [35] and Przybył *et al*. [36] also demonstrated that combining CNN with computer vision can accurately identify coffee bean quality. Micaraseth *et al*. [37] employed three CNN models for coffee defect detection, achieving high accuracy and short detection times with all three models. In addition to shortening processing times, Chen *et al*. [38] demonstrated that a multimodal real-time algorithm using CNN and a near-infrared snapshot hyperspectral sensor for coffee bean detection could reduce labor costs while maintaining high accuracy. The use of CNN to improve defect detection accuracy in coffee beans has also been proven by Pinto *et al*. [39], who classified coffee beans into six types of defects, increasing accuracy from 72 to 98%. In this study, the automatic detection of Indonesian coffee bean types is conducted by developing and applying a visual-based deep learning method using CNN.

This study makes several key contributions to the field of coffee bean classification. First, it utilizes a dataset consisting of 116 types of single-origin coffee, which, to the best of our knowledge, is the largest dataset of Indonesian coffee varieties compiled to date. This extensive dataset provides a comprehensive foundation for analyzing the diverse characteristics of Indonesian coffee beans. Second, the dataset was captured using a standard digital camera, avoiding the need for complex and costly imaging setups, making the method more accessible and replicable for other researchers and practitioners. Finally, this study involves the creation and development of CNN models specifically designed for the visual prediction of coffee bean types using this dataset. These CNN models are optimized to deliver accurate classifications, thereby advancing the use of AI in the coffee industry and contributing to the broader goal of improving efficiency and precision in coffee bean sorting processes.

## 3. METHODS

This study develops prediction models using two different methods. The first method is transfer learning, which utilizes the pretrained Inception V3 model. The second method involves building a model from scratch, with preprocessing applied in both to align the dataset with the research objectives.

### 3.1. Data preprocessing

Several preprocessing steps were carried out, as shown in Figure 1, including shuffling the data and splitting it into training, validation, and testing sets. Afterward, resizing, rescaling, and data augmentation were performed. The data shuffling process was done randomly across the dataset. This was followed by resizing and rescaling the data. Additionally, augmentation was only applied to the training data to introduce more variation and improve the model's performance during training.

### 3.2. Transfer learning model

The model development process involves transfer learning, utilizing the pretrained Inception V3 model along with weights obtained from previous training on different datasets. Two fine-tuning scenarios are applied during training: in the first scenario, half of the feature extraction layers are unfrozen, while in the second scenario, all the layers are unfrozen. The Inception V3 model was selected due to its high accuracy when trained on the ImageNet dataset and its complex architecture, which includes 23.9 million parameters. The details of the training scenarios are as follows.

Scenario 1. In the first scenario, the model is trained by freezing all feature extraction layers and replacing the classification layer to suit the specific task of coffee classification. Consequently, the weights in the feature extraction layers remain unchanged. This step aims to train the classification layer to align with the objectives of this model development. The training process is carried out for 25 epochs, representing half of the total epochs planned for model training. Afterward, half of the feature extraction layers are unfrozen, allowing for weight updates in these layers. This fine-tuning step is performed to adjust the previously pretrained weights to the current dataset, with another 25 epochs of training. This approach optimizes the model for the specific classification task in this research.

Scenario 2. In the second scenario, all feature extraction layers are unfrozen, and the classification layer is replaced to suit the coffee classification task. This adjustment allows the entire model to learn from scratch, accounting for potential differences in the datasets used in previous training. As a result, the weights will be updated at each stage of the training process, which is conducted over 50 epochs. Inception V3. This pretrained model is an advancement by Szegedy *et al*. [40] over the previous Inception model and was trained on the ImageNet dataset. Inception V3 comprises convolutional blocks, Inception modules, and a classifier, with a total of 48 layers. The architecture of this model is shown in Figure 2.

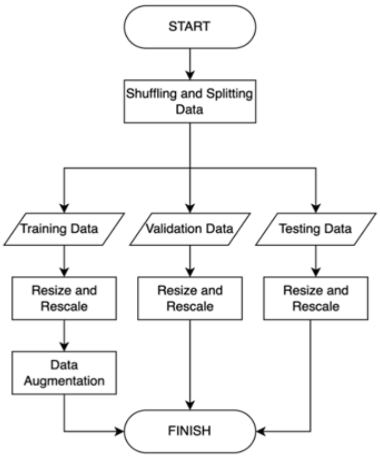



Figure 1. Data preprocessing stages

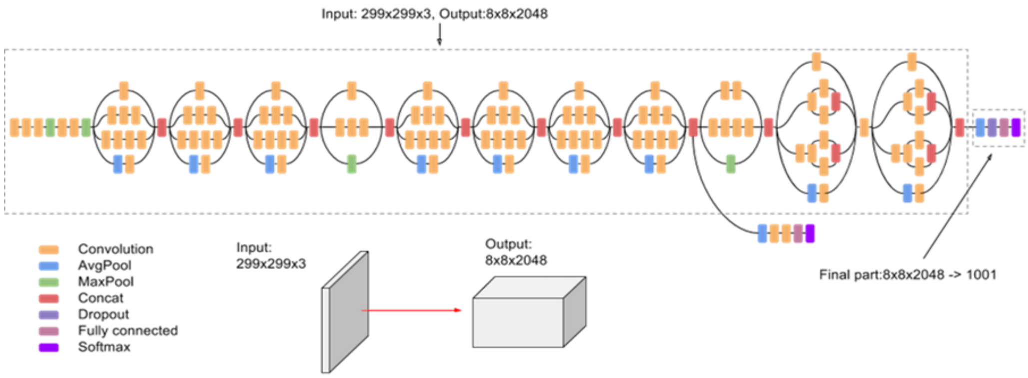



Figure 2. Architecture of Inception V3 [41]

### 3.3. Training from scratch model

The build-from-scratch approach involves designing the model architecture from the ground up. The developed structure consists of feature extraction layers, where each convolutional layer has a specific number and size of filters, followed by a max pooling layer. To optimize the model's architecture, the Taguchi method is applied using a design of experiment (DoE) approach, aiming to find a robust combination of the number of feature extraction layers and training epochs. The process flow is illustrated in Figure 3.

The process begins with problem formulation, where the goal is to find the optimal combination between the number of training epochs and feature extraction layers used. The output indicator will be the accuracy achieved on the validation data during the final epoch of model training, with the goal of maximizing this value. Next, control factors are identified: the number of training epochs, which affects the risk of underfitting or overfitting, and the number of feature extraction layers, which impacts the depth of the model's architecture. Then, experiments are conducted using combinations of these factors based on a predefined design. Using the L9 orthogonal array, nine combinations with three levels are identified: the number of epochs set at 50, 75, and 100, and the number of feature extraction layers set at 5, 6, and 7. The training process is carried out using the same equipment to minimize noise. The experiment is analyzed based on the signal-to-noise (S/N) ratio, with the "larger is better" criterion used to maximize accuracy. This approach helps identify a robust combination that will yield the highest model accuracy. The results of this analysis serve as the basis for model development.

### 3.4. Model performance evaluation indicators

Several indicators are used to analyze the performance of the developed model. If the model is found lacking based on the indicators listed in Table 1, a hyperparameter tuning process will be initiated. The key indicators used to assess whether a model is considered optimal include achieving the highest accuracy, precision, and recall, with the lowest possible loss, while avoiding signs of overfitting or underfitting during training and validation. Additionally, the model must exhibit strong performance on the test data, as demonstrated by high values in accuracy, precision, recall, and F1-score. Computation time, especially for testing data, is also a crucial factor when determining which model to apply to real-world problems, as faster models may be more practical for implementation.

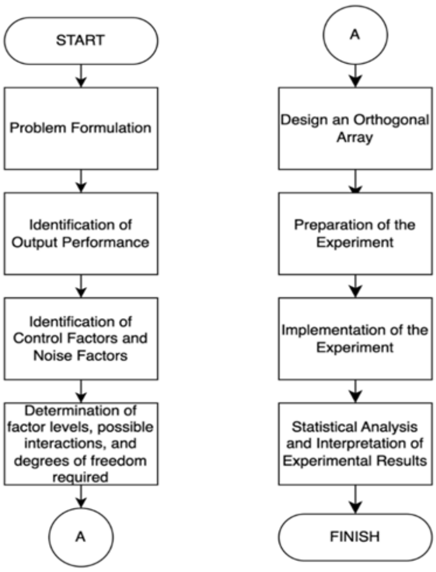



Figure 3. Taguchi methodd process flow

Table 1. Model performance evaluation indicators

| Parameter | Indicator |
|---|---|
| Training result | The average values of loss, accuracy, precision, and recall on the training and validation data, as well as the training time. |
| Testing result | Analysing the average accuracy, precision, recall, and F1-score for both classes, along with the testing time. |

## 4. EXPERIMENTS AND RESULTS

### 4.1. Dataset

This study utilizes a dataset consisting of photos collected based on various types of coffee beans from across Indonesia. Broadly speaking, there are four main types of coffee beans: Arabica, Robusta, Liberica, and Excelsa. The dataset includes 116 distinct types of coffee beans categorized by their growing regions, comprising a total of 14,525 images. Figure 4 presents representative examples of three Indonesian coffee bean types—Robusta Dampit in Figure 4(a), Arabica Cihurip in Figure 4(b), and Liberica Sumedang in Figure 4(c)—selected from a total of 116 varieties included in the dataset. These examples highlight the notable morphological and color variations among coffee beans originating from different regions and species, illustrating the visual diversity that the classification model must recognize. The details of datasets are presented in Table 2.

(a) (b) (c)

Figure 4. Examples of the images from three coffee varieties of (a) Robusta Dampit, (b) Arabica Cihurip, and (c) Liberica Sumedang

Table 2. Details of the datasets

| Type of coffee beans | Number of data | Type of coffee beans | Number of data |
|---|---|---|---|
| Liberica Lawu | 209 | Arabica Pandansari Brebes | 116 |
| Robusta Lawu | 172 | Robusta Merapi | 112 |
| Arabica Flores Bajawa Wash | 168 | Robusta Temanggung Natural | 112 |
| Arabica Ciwidey Wine | 164 | Arabica Argopuro | 112 |
| Arabica Papua Dogiyai | 164 | Arabica Temanggung Honey | 111 |
| Arabica Gunung Sumbing | 164 | Arabica Merapi Wine | 111 |
| Arabica Mewarwangi | 164 | Robusta Medan | 110 |
| Arabica Wanoja Kamojang | 164 | Robusta Flores | 110 |
| Excelsa Gunung Sindoro | 164 | Arabica Lawu | 109 |
| Arabica Puntang Jawa Barat | 163 | Arabica Aceh Gayo Honey | 108 |
| Excelsa Ijen Raung | 162 | Robusta Dampit | 108 |
| Arabica Toraja Rantekarua | 160 | Arabica Ciwidey Luwak | 108 |
| Arabica Ijen Carbonic Mascerasi Natural | 156 | Arabica Gowa Malino Speciality | 108 |
| Arabica Toraja Napo | 156 | Arabik Subang Natural | 108 |
| Robusta Mandailing Sumatra | 154 | Arabica Rancabali Honey | 106 |
| Arabica Enrekang Latimojong | 154 | Arabica Bengkulu | 106 |
| Arabica Gn. Patuha | 154 | Arabica Toraja Fullwash | 104 |
| Arabica Lintong Nihuta | 152 | Robusta Lampung | 104 |
| Arabica Flores Manggarai | 152 | Arabica Temanggung Fullwash | 104 |
| Arabica Mamasa | 152 | Arabica Klaten Yellow Bourbon | 104 |
| Arabica Gunung Tilu | 152 | Robusta Ijen Carbonic Mascerasi Natural | 104 |
| Arabica Cihurip | 152 | Arabica Luwak Aceh Gayo | 104 |
| Arabica Bali Kintamani | 152 | Arabica Gunung Halu | 104 |
| Arabica Ciwidey Natural | 148 | Robusta Magelang Semar Mesem | 104 |
| Arabica Ciwidey Honey | 148 | Robusta Bali Kintamani | 104 |
| Robusta Gunung Ungaran | 148 | Arabica Bali Premium | 103 |
| Arabica Gn. Halimun Sukabumi | 148 | Robusta Sumbawa | 102 |
| Robusta Wonogiri | 148 | Robusta Bali Pupuan | 102 |
| Arabica Java Carlos Wash | 148 | Arabica Flores Juria Manggarai | 102 |
| Robusta Gunung Kelir | 146 | Robusta Toraja Kalosi | 101 |
| Liberica Sumedang | 144 | Robusta Fine Garut | 101 |
| Arabica Burangrang | 140 | Arabica Temanggung Anaerob | 101 |
| Arabica Ijen Honey | 140 | Robusta Sidikalang Sumatra | 100 |
| Arabica Argopuro Damarkandang Carbonic Mascerasi | 140 | Robusta Wine Temanggung | 100 |
| Liberica Gunung Muria | 138 | Arabica Dampit | 100 |
| Arabica Timor Leste Ermera | 136 | Robusta Papua Ambaidiru | 100 |
| Robusta Aceh Lamno | 136 | Robusta Solok Padang | 100 |
| Arabica Semeru | 136 | Robusta Kudus | 100 |
| Arabica Samosir | 136 | Arabica Gunung Halu Fullwash | 100 |
| Arabica Gunung Sindoro | 132 | Arabica Java Ijen Natural | 100 |
| Arabica Enerekang | 132 | Robusta Lanang Dampit | 100 |
| Arabica Wonogiri | 132 | Robusta Java Carlos Malang | 100 |
| Arabica Toraja Sapan | 132 | Arabica Minang Solok | 100 |
| Arabica Cikuray | 132 | Robusta Gayo Aceh | 100 |
| Arabica Aceh Gayo Jagong Jeget Anaerob Natural | 132 | Arabica Papua Yahokimo | 100 |
| Arabica Gunung Arjuna Anaerob 120 H Natural | 130 | Robusta Fine Pagaralam | 100 |
| Arabica Papua Wamena | 128 | Arabica Puntang Natural | 100 |
| Robusta Ciwidey | 128 | Arabica Sumbawa | 100 |
| Robusta Gunung Arjuna | 126 | Robusta Wonosalam | 96 |
| Arabica Gayo Fullwash | 124 | Arabica Manglayang | 80 |
| Arabica Mandheling | 124 | Liberica Jambi | 120 |
| Excelsa Wonosalam | 124 | Excelsa Wonogiri | 120 |
| Arabica Aceh Gayo Avatara Thermal Natural | 124 | Arabica Gunung Prau | 120 |
| Arabica Java Carlos Natural | 124 | Arabica Bali Buleleng Anaerob | 120 |
| Robusta Kerinci | 124 | Robusta Papua Mimika | 118 |
| Arabica Sidikalang | 124 | Arabica Aceh Gayo Mondel | 116 |
| Arabica Semendo | 124 | Arabica Garut Don Obar Lavender | 116 |
| Arabica Flores Bajawa Full Wash | 120 | Robusta Bengkulu | 116 |

### 4.2. Data preprocessing
#### 4.2.1. Shuffling and splitting data

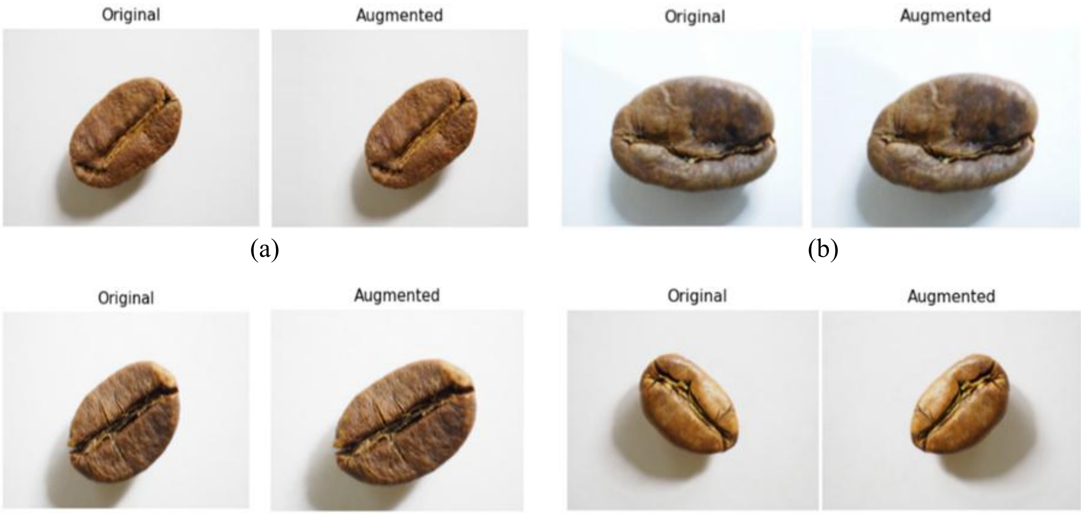
Shuffling is a step used to randomly rearrange the dataset based on a random parameter. This process is done simultaneously with the data splitting step. By doing so, the data is shuffled and then divided into training, validation, and test sets. The purpose of this division is to ensure that the test data has not been used in the training set, and vice versa. Shuffling and splitting are expected to help the model learn the data without relying on a specific order, but instead on the complex patterns within the data. The data is split into 80% training, 10% validation, and 10% test sets, resulting in 11,620 training images, 1,452 validation images, and 1,453 test images. The large training set is intended to help the model better understand the variables in the data, preventing both overfitting and underfitting.

#### 4.2.2. Resize and rescale

The resizing step involves setting the image dimensions to 150×150 pixels. This ensures that all data has a uniform size. Next, normalization is applied to convert pixel values into a matrix of values ranging between zero and one, using the parameter 1/255.

#### 4.2.3. Data augmentation

Data augmentation is applied to increase the variety of datasets. To enhance the robustness and generalization capability of the model, several data augmentation techniques as shown in Figure 5 were applied to the training dataset. These include height shift in Figure 5(a), shear in Figure 5(b), zoom in Figure 5(c), and horizontal flip transformations in Figure 5(d). In each subfigure, the image on the left represents the original coffee bean, while the image on the right shows the corresponding augmented version, demonstrating how these techniques increase the diversity of the dataset. These steps generate new images to enrich the training dataset, enhancing the model's ability to generalize.




(a) (b) (c) (d)

Figure 5. Data augmentation techniques of (a) height shift, (b) shear, (c) zoom, and (d) horizontal flip

### 4.3. Hyperparameter settings

Several hyperparameters applied to the model have been predetermined, as shown in Table 3. These settings were standardized across all models being trained to ensure fair treatment and facilitate comparisons. The Inception V3 transfer learning model was trained for 50 epochs, while the number of epochs for the build-from-scratch model was determined through Taguchi experiments. The model development was carried out using TensorFlow, with the code written in Python. The training process was conducted using Jupyter Notebook on a computer equipped with an Intel Core i9-13900KF 3GHz CPU, 32 GB of RAM, and an NVIDIA GeForce RTX 4080 GPU.

### 4.4. Architecture of transfer learning with Inception V3

In scenario 1, the feature extraction layers are frozen, utilizing the pretrained weights of Inception V3. This approach focuses on training only the classification part of the model. The number of epochs used in this phase is 25. After that, fine-tuning is performed by unfreezing half of the feature extraction layers, specifically 155 out of the total 311 layers. This fine-tuning phase also runs for 25 epochs, bringing the total training epochs for this scenario to 50. In scenario 2, all the feature extraction layers are unfrozen. This approach allows the model to learn the dataset from the very first layer, addressing any significant differences between the dataset used in this study and the one used for pretraining the model. The difference in the number of parameters can be seen in Table 4, and the model architecture of transfer learning is illustrated in Figures 6—Figure 6(a) for scenario 1 with all layers frozen, Figure 6(b) for scenario 1 with half of the layers unfrozen, and Figure 6(c) for scenario 2.

Table 3. Hyperparameter settings

| Hyperparameter | Value |
|---|---|
| Loss function | Binary crossentropy |
| Batch size | 256 |
| Optimizer | Adam |
| Input size | 192×75 |
| Learning rate | 0.01 |
| Evaluation metric | Accuracy, precision, recall |

Table 4. Number of transfer learning models parameters

| Scenario | Stages | Parameter type | |
|---|---|---|---|
| | | Trainable | Non-trainable |
| #1 | Freeze all layer | 2,107,401 | 21,802,784 |
| | Unfreeze half layer | 18,896,841 | 5,013,344 |
| #2 | Unfreeze all layer | 23,867,553 | 34,432 |

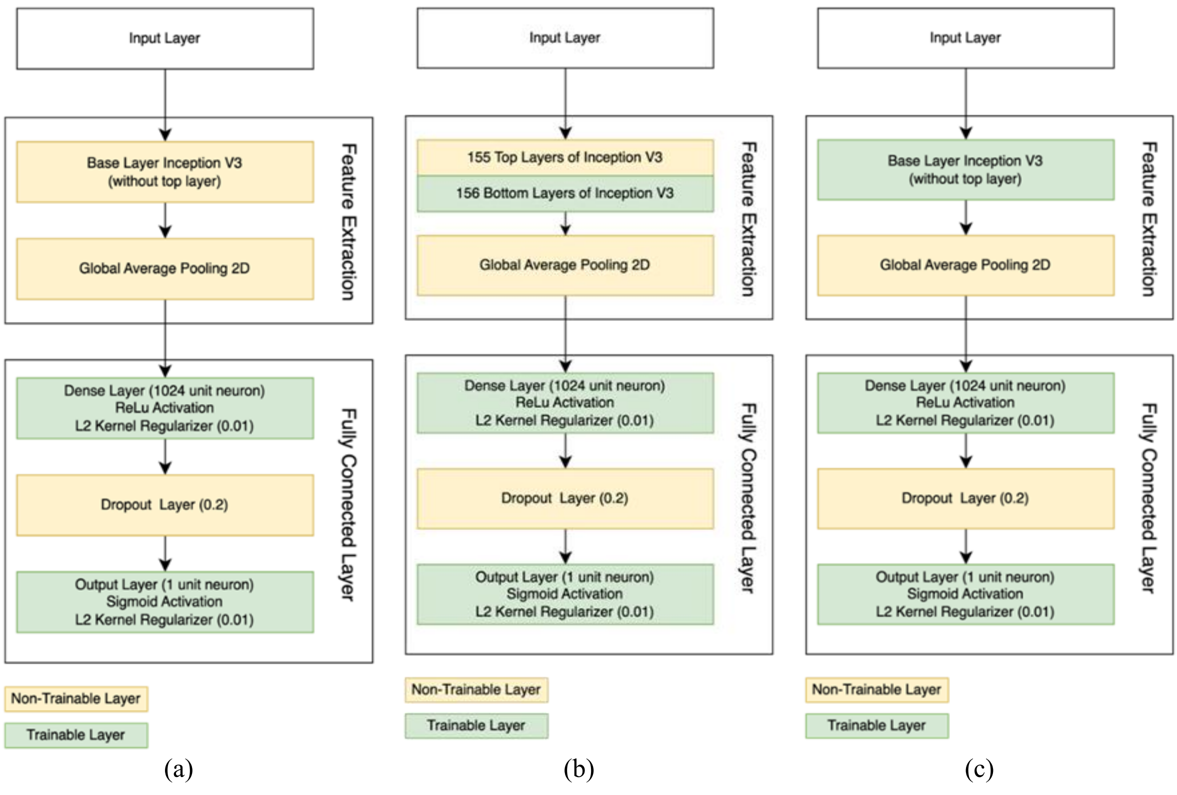



Figure 6. Architecture of transfer learning model of (a) scenario 1: freeze all layer, (b) scenario 1: unfreeze half layer, and (c) scenario 2: unfreeze half layer

### 4.5. Architecture of training from scratch model

The architecture development for the build-from-scratch model was carried out based on the analysis using the Taguchi method, resulting in a robust combination of the number of feature extraction layers and the training epochs. The feature extraction layers analyzed consisted of 5, 6, and 7 convolutional layers. The first three layers are identical, followed by layers 4, 5, 6, and 7, each containing 64 filters with a size of 3×3, applying the ReLU activation function. Padding is applied to all layers except the third convolutional layer. Each convolutional layer is followed by a 2×2 pooling layer. Meanwhile, the number of epochs tested includes 50, 75, and 100 epochs. Validation accuracy is used as the evaluation output, based on the S/N ratio, with the "larger is better" approach. Details of the factor combinations are shown in Table 5, and the analysis results are presented in Figure 7.

The Taguchi analysis revealed that the most robust combination for the model consists of 7 feature extraction layers and 100 training epochs. This combination yields the highest accuracy compared to other tested configurations. Based on this result, the developed model will have an architecture consisting of 7 convolutional layers. The first layer will have 16 filters, the second layer will have 32 filters, and the remaining layers will have 64 filters, all with a filter size of 3×3. Each convolutional layer is followed by a max-pooling layer with a pool size of 2×2. This structure is then connected to a global average pooling layer, which converts the feature matrix into a vector that is passed to a fully connected layer. The first fully connected layer has 512 neurons, while the second fully connected layer has 116 neurons. Each layer uses the ReLU activation function, except for the final layer, which utilizes Softmax for multiclass classification. The model contains a total of 264,084 trainable parameters and will be trained for 100 epochs. The model architecture is illustrated in Figure 8.

Table 5. Design of experiment results for training from scratch model

| Number of feature extraction layer | Number of epoch | Validation accuracy (%) |
|---|---|---|
| 5 | 50 | 49.45 |
| 5 | 75 | 55.44 |
| 5 | 100 | 55.99 |
| 6 | 50 | 51.17 |
| 6 | 75 | 56.47 |
| 6 | 100 | 63.50 |
| 7 | 50 | 54.89 |
| 7 | 75 | 62.40 |
| 7 | 100 | 67.98 |

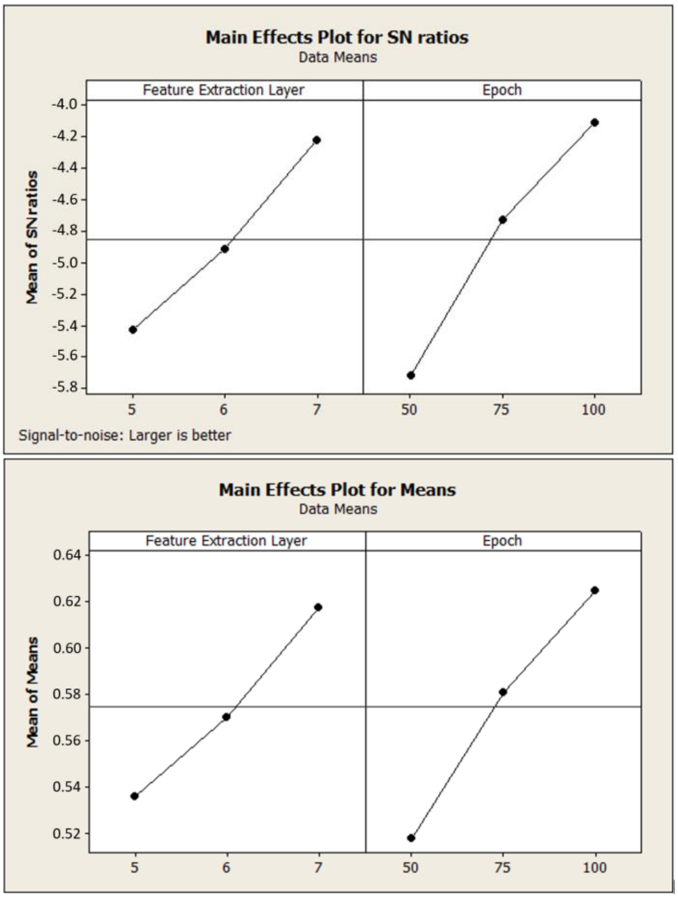



Figure 7. Taguchi analysis

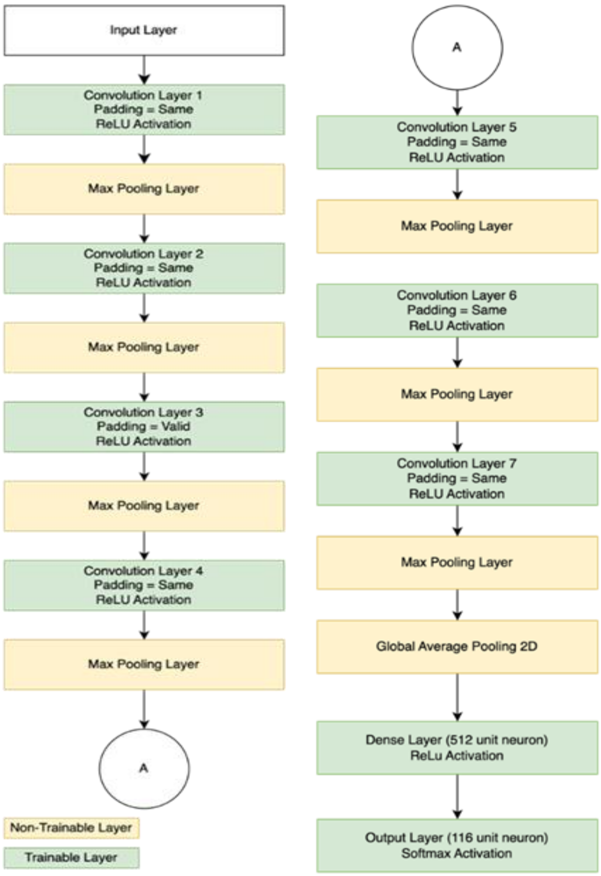



Figure 8. Architecture of training from scratch model

## 4.6. Training results

The training phase was carried out for 50 epochs on the Inception V3 transfer learning model in both scenarios. Meanwhile, the build-from-scratch model was trained for 100 epochs, as determined by the Taguchi method analysis. The training process for the Inception V3 transfer learning model in scenario 1, scenario 2, and the build-from-scratch model is shown in Figures 9 to 11, respectively.

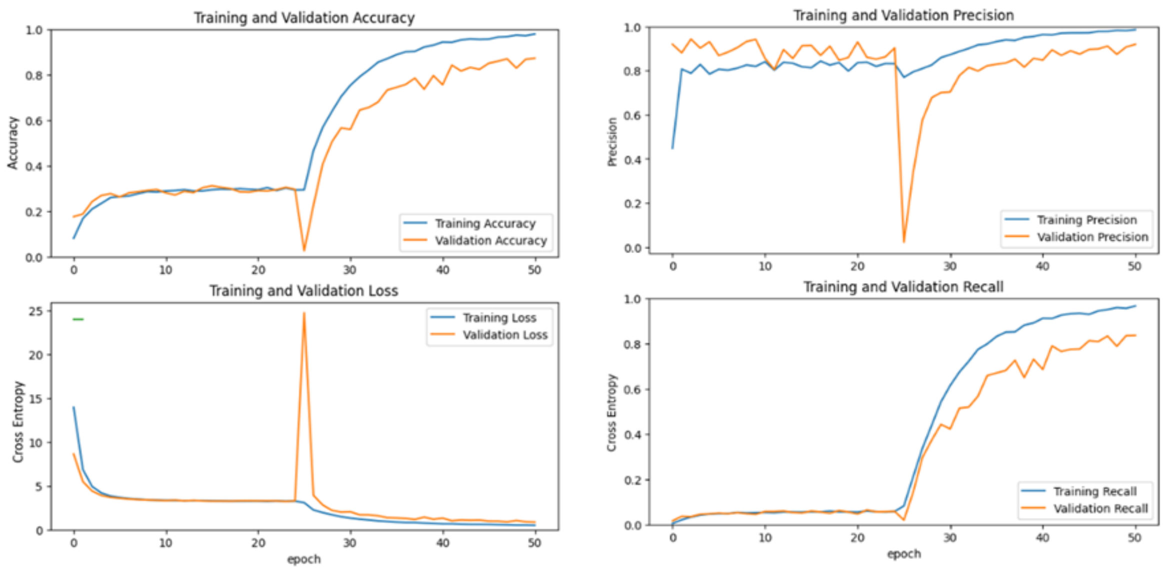



Figure 9. Training progress of Inception V3 model using scenario 1

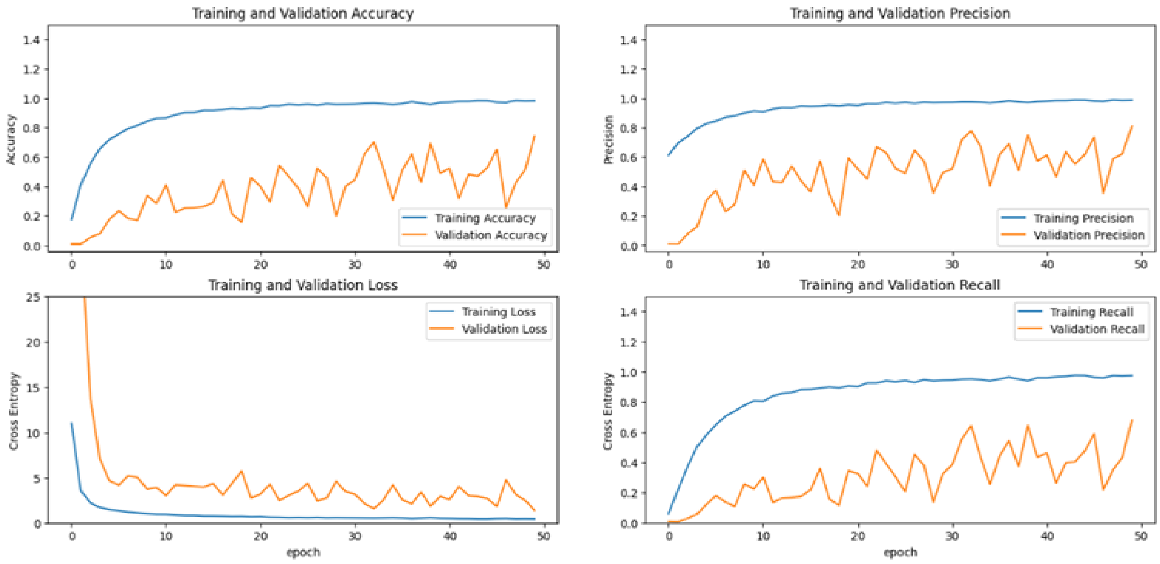



Figure 10. Training progress of Inception V3 model using scenario 2

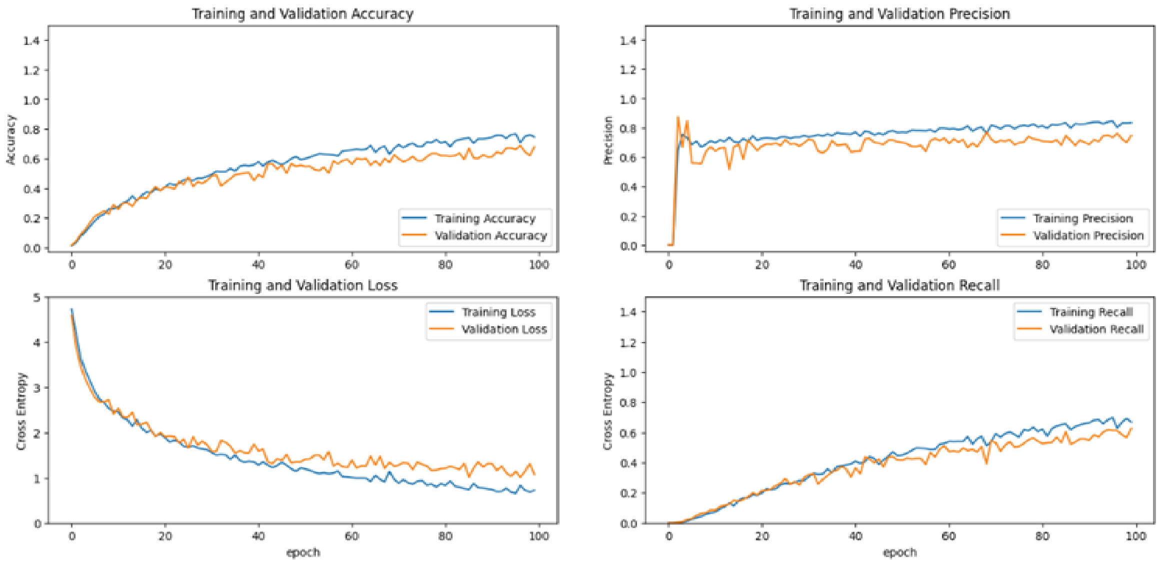



Figure 11. Training progress of training from scratch model

During the training process, the models were evaluated based on their performance on the validation data. The results showed that across all models, accuracy increased while loss decreased after training. This indicates that the models underwent effective training, adapting well to new data and achieving more accurate predictions. The graphs for the three models displayed relatively close movements between the training and validation data, suggesting that there were no signs of overfitting or underfitting.

Furthermore, when considering evaluation metrics such as loss, accuracy, precision, and recall at the end of the training for each model as seen in Figure 12, it is clear that the Inception V3 transfer learning model in scenario 1 delivered the most optimal results compared to the other two models. Although its training loss was higher than that of scenario 2 of the Inception V3 transfer learning model, it outperformed in the other metrics, demonstrating that its learning process was the most effective. Based on the average training time, as shown in Figure 13, the Inception V3 transfer learning model emerged as the best in terms of efficiency, with the shortest training time of 45 minutes. This efficiency is due to the model utilizing pretrained weights. In contrast, the training processes for Inception V3 in scenario 2 and the build-from-scratch model took relatively longer because the entire model was trained on the training data. Inception V3 scenario 2 had the longest training time, at 204.2 minutes, due to its more complex architecture compared to the build-from-scratch model.

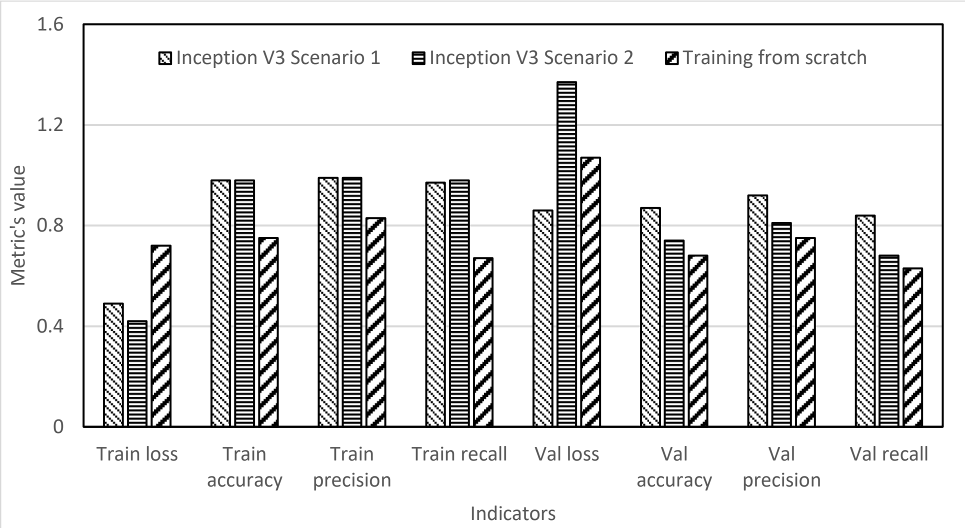



Figure 12. Training result evaluation matrix comparison

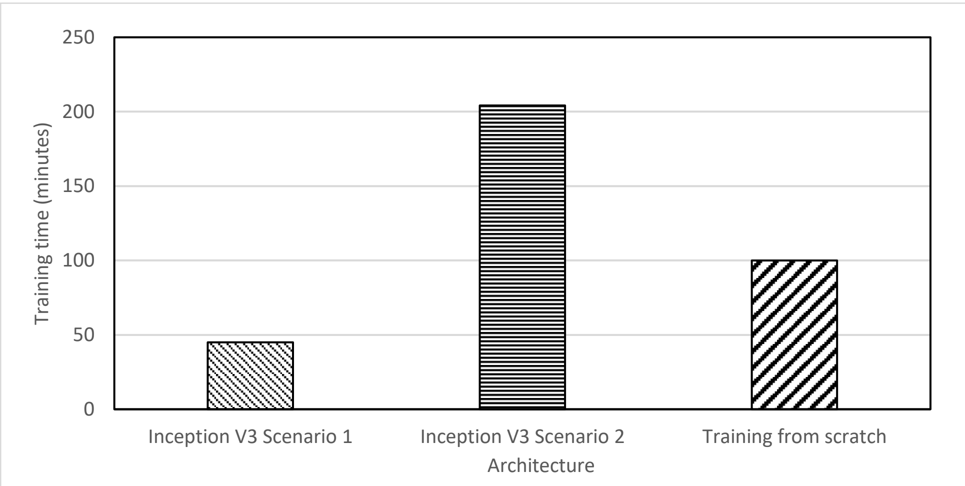



Figure 13. Average training time comparison

### 4.7. Testing results

The testing phase was conducted to evaluate the model's ability to detect new data. As shown in Figure 14, the best-performing model was the Inception V3 transfer learning model in scenario 1, achieving an accuracy of 0.87. In comparison, Inception V3 in scenario 2 achieved an accuracy of 0.75, while the testing phase was conducted to evaluate the model's ability to detect new data. As shown in Figure 14, the best-performing model was the Inception V3 transfer learning model in scenario 1, achieving an accuracy of 0.87. In comparison, Inception V3 in scenario 2 achieved an accuracy of 0.75, while the build-from-scratch model had the lowest accuracy at 0.69. Thus, the Inception V3 transfer learning model in scenario 1 demonstrated superior performance in detecting new data compared to the other models.

This result is consistent with other evaluation metrics. For precision, the Inception V3 transfer learning model in scenario 1 outperformed the others with a score of 0.92, while scenario 2 and the build-from-scratch model scored 0.83 and 0.76, respectively. Similarly, the recall metric showed that the Inception V3 transfer learning model in scenario 1 had the best performance with a value of 0.83, followed by scenario 2 with 0.69, and the build-from-scratch model with 0.64.

To harmonize the values of precision and recall, the F1-score was also calculated. The F1-score for Inception V3 transfer learning in scenario 1 was the highest at 0.87, while scenario 2 and the build-from-scratch model had scores of 0.76 and 0.70, respectively. This confirms that the Inception V3 transfer learning model in scenario 1 is the best overall performer.

The analysis also includes the time taken by each model to detect a single image, as shown in Figure 15. The Inception V3 transfer learning model in scenario 2 had the longest testing time, taking 7.30 seconds per image. A similar result was observed with Inception V3 scenario 1 due to the high complexity of the model's architecture. In contrast, the build-from-scratch model required the shortest time, at just 1.80 seconds per image, owing to its simpler architecture compared to the other two models.

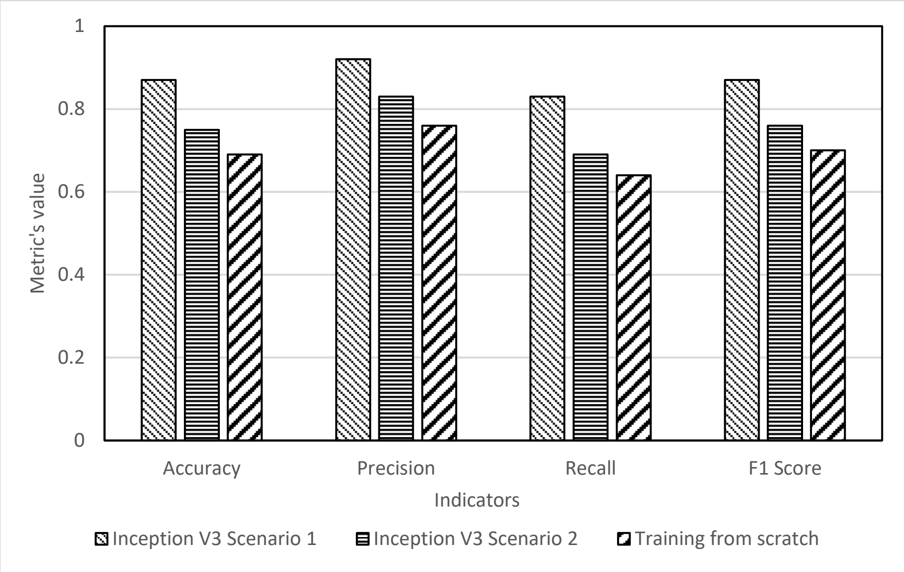



Figure 14. Testing result evaluation matrix comparison

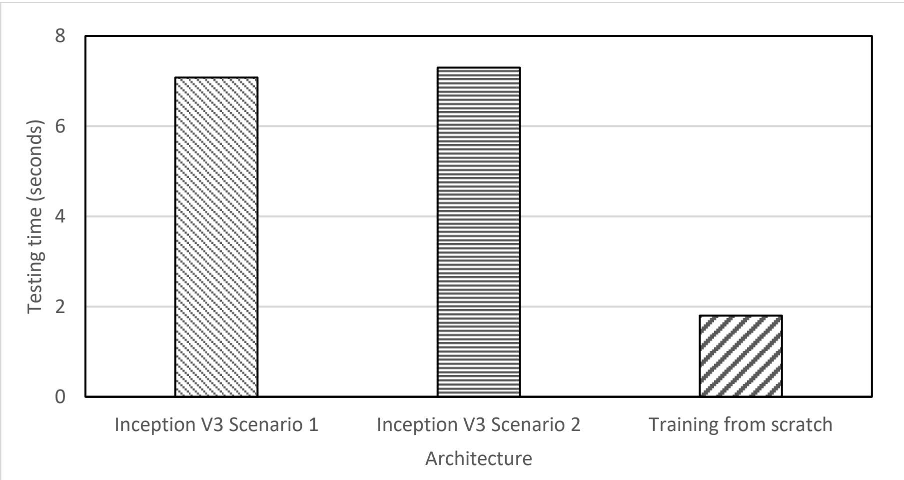



Figure 15. Testing time comparison

Beyond laboratory testing, the developed CNN-based classification model holds strong potential for integration with digital coffee sorting systems and mobile applications used by farmers and cooperatives. By embedding the trained model into portable or cloud-connected devices, coffee producers could perform real-time classification directly at the farm or cooperative level, reducing dependence on expert cuppers and minimizing manual errors. The model’s lightweight architecture and compatibility with edge computing frameworks make it suitable for deployment on smartphones or automated optical sorting systems. Such integration can streamline post-harvest processes, ensure consistent quality control, and enhance traceability across Indonesia's diverse coffee value chain.

The implementation of AI-driven coffee bean classification systems such as the one developed in this study also holds significant implications for export quality control and traceability in global coffee markets. Automated and objective classification enables standardized quality assessment aligned with international grading systems, reducing variability introduced by manual inspection. Moreover, by linking digital classification results to batch-level identifiers or blockchain-based traceability systems, exporters and cooperatives can provide verifiable data on bean type, origin, and processing method.

## 5. CONCLUSION

This study successfully developed a CNN model for classifying 116 types of Indonesian coffee beans using a dataset of 14,525 images. Data preprocessing involved resizing, rescaling, and augmentation to improve dataset quality and diversity, with an 80–10–10 split for training, validation, and testing. Two modeling approaches were explored—transfer learning with Inception V3 and a model built from scratch—where the fine-tuned Inception V3 (scenario 1) achieved the best performance, recording a test accuracy of 0.87 and superior precision, recall, and F1-scores. The proposed model demonstrates strong potential for integration into digital sorting systems and mobile applications to assist farmers and cooperatives, while its application also supports standardized export quality control and traceability in global coffee markets.

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.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## AUTHOR CONTRIBUTIONS STATEMENT

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|---|---|---|
| C : **C**onceptualization | I : **I**nvestigation | Vi : **Vi**sualization |
| M : **M**ethodology | R : **R**esources | Su : **Su**pervision |
| So : **So**ftware | D : **D**ata Curation | P : **P**roject administration |
| Va : **Va**lidation | O : Writing - **O**riginal Draft | Fu : **Fu**nding acquisition |
| Fo : **Fo**rmal analysis | E : Writing - Review & **E**diting | |


## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.


## DATA AVAILABILITY

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

## REFERENCES


[1] N. M. Ibrahim, D. G. I. Gabr, A. ur Rahman, S. Dash, and A. Nayyar, "A deep learning approach to intelligent fruit identification and family classification," *Multimedia Tools and Applications*, vol. 81, no. 19, pp. 27783–27798, 2022, doi: 10.1007/s11042-022-12942-9.

[2] BPS-Statistics Indonesia, *Statistical yearbook of Indonesia*. Jakarta, Indonesia: BPS-Statistics Indonesia, 2023.

[3] BPS-Statistics Indonesia, *Indonesia coffee statistics 2022*. Jakarta, Indonesia: BPS-Statistics Indonesia, 2023.

[4] W. Dong, R. Hu, Z. Chu, J. Zhao, and L. Tan, "Effect of different drying techniques on bioactive components, fatty acid composition, and volatile profile of Robusta coffee beans," *Food Chemistry*, vol. 234, pp. 121–130, 2017, doi: 10.1016/j.foodchem.2017.04.156.

[5] A. M. F.-Morales, "Examining the case of green coffee to illustrate the limitations of grading systems/expert tasters in sensory evaluation for quality control," *Food Quality and Preference*, vol. 13, no. 6, pp. 355–367, 2002, doi: 10.1016/S0950-3293(02)00028-9.

[6] E. Hassan, "Enhancing coffee bean classification: a comparative analysis of pre-trained deep learning models," *Neural Computing and Applications*, vol. 36, no. 16, pp. 9023–9052, 2024, doi: 10.1007/s00521-024-09623-z.

[7] I. V. C. Motta, N. Vuillerme, H.-H. Pham, and F. A. P. de Figueiredo, "Machine learning techniques for coffee classification: a comprehensive review of scientific research," *Artificial Intelligence Review*, vol. 58, no. 1, 2024, doi: 10.1007/s10462-024-11004-w.

[8] J. Livio and R. Hodhod, "AI cupper: a fuzzy expert system for sensorial evaluation of coffee bean attributes to derive quality scoring," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 6, pp. 3418–3427, 2018, doi: 10.1109/TFUZZ.2018.2832611.

[9] F. F. L. Dos Santos, J. T. F. Rosas, R. N. Martins, G. de M. Araújo, L. de A. Viana, and J. de P. Gonçalves, "Quality assessment of coffee beans through computer vision and machine learning algorithms," *Coffee Science*, vol. 15, no. 1, pp. 1–9, 2020, doi: 10.25186/.v15i.1752.

[10] E. R. Arboleda, A. C. Fajardo, and R. P. Medina, "Classification of coffee bean species using image processing, artificial neural network and k nearest neighbors," in *2018 IEEE International Conference on Innovative Research and Development, ICIRD 2018*, 2018, pp. 1–5, doi: 10.1109/ICIRD.2018.8376326.

[11] M. García, J. E. C.- Becerra, and F. E. Hoyos, "Quality and defect inspection of green coffee beans using a computer vision system," *Applied Sciences*, vol. 9, no. 19, 2019, doi: 10.3390/app9194195.

[12] D. B. Magfira and R. Sarno, "Classification of Arabica and Robusta coffee using electronic nose," *2018 International Conference on Information and Communications Technology*, pp. 645–650, Mar. 2018, doi: 10.1109/ICOIACT.2018.8350725.

[13] M. V. C. Caya, R. G. Maramba, J. S. D. Mendoza, and P. S. Suman, "Characterization and classification of coffee bean types using support vector machine," *IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management*, 2020, doi: 10.1109/HNICEM51456.2020.9400144.

[14] J. P. L. Pizzaia, I. R. Salcides, G. M. De Almeida, R. Contarato, and R. De Almeida, "Arabica coffee samples classification using a multilayer perceptron neural network," *13th IEEE International Conference on Industry Applications*, pp. 80–84, 2018, doi: 10.1109/INDUSCON.2018.8627271.

[15] M. Hakim, T. Djatna, and I. Yuliasih, "Deep learning for roasting coffee bean quality assessment using computer vision in mobile environment," *International Conference on Advanced Computer Science and Information Systems (*, pp. 363–370, 2020, doi: 10.1109/ICACSIS51025.2020.9263224.

[16] E. Aghdamifar, V. R. Sharabiani, E. Taghinezhad, M. Szymanek, and A. D.- Hunek, "E-nose as a non-destructive and fast method for identification and classification of coffee beans based on soft computing models," *Sensors and Actuators B: Chemical*, vol. 393, 2023, doi: 10.1016/j.snb.2023.134229.

[17] D.-G. Lee and Y. Jung, "Tutorial and applications of convolutional neural network models in image classification," *Journal of the Korean Data And Information Science Society*, vol. 33, no. 3, pp. 533–549, 2022, doi: 10.7465/jkdi.2022.33.3.533.

[18] T. H. Nasution and U. Andayani, "Recognition of roasted coffee bean levels using image processing and neural network," *IOP Conference Series: Materials Science and Engineering*, vol. 180, no. 1, 2017, doi: 10.1088/1757-899X/180/1/012059.

[19] D. Suhandy and M. Yulia, "The potential of UV-visible spectroscopy and chemometrics for determination of geographic origin of three specialty coffees in Indonesia," *AIP Conference Proceedings*, vol. 2021, 2018, doi: 10.1063/1.5062745.

[20] C. H. Lee, I. Te Chen, H. C. Yang, and Y. J. Chen, "An AI-powered electronic nose system with fingerprint extraction for aroma recognition of coffee beans," *Micromachines*, vol. 13, no. 8, 2022, doi: 10.3390/mi13081313.

[21] D. H. Suryana and W. K. Raharja, "Applying artificial intelligence to classify the maturity level of coffee beans during roasting," *International Journal of Engineering, Science and Information Technology*, vol. 3, no. 2, pp. 97–105, 2023, doi: 10.52088/ijesty.v3i2.461.

[22] S. P. Pragathi and L. Jacob, "Review on image based coffee bean quality classification: machine learning approach," *Proceedings - 2022 4th International Conference on Advances in Computing, Communication Control and Networking*, pp. 706–711, 2022, doi: 10.1109/ICAC3N56670.2022.10074124.

[23] B. T. W. Putra, R. Amirudin, and B. Marhaenanto, "The evaluation of deep learning using convolutional neural network (CNN) approach for identifying Arabica and Robusta coffee plants," *Journal of Biosystems Engineering*, vol. 47, no. 2, pp. 118–129, 2022, doi: 10.1007/s42853-022-00136-y.

[24] A. Kamilaris and F. X. P.- Boldú, "Deep learning in agriculture: a survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018, doi: 10.1016/j.compag.2018.02.016.

[25] I. M. Nasir *et al.*, "Deep learning-based classification of fruit diseases: an application for precision agriculture," *Computers, Materials and Continua*, vol. 66, no. 2, pp. 1949–1962, 2020, doi: 10.32604/cmc.2020.012945.

[26] O. J. Algani, Y. M. A. Caro, Marquez, L. M. R. Bravo, C. Kaur, M. S. Al Ansari, and B. K. Bala, "Leaf disease identification and classification using optimized deep learning," *Measurement: Sensors*, vol. 25, 2023, doi: 10.1016/j.measen.2022.100643.

[27] M. Jumarlis, M. Mirfan, and A. R. Manga, "Classification of coffee bean defects using gray-level co-occurrence matrix and k-nearest neighbor," *ILKOM Jurnal Ilmiah*, vol. 14, no. 1, pp. 1–9, 2022, doi: 10.33096/ilkom.v14i1.910.1-9.

[28] L. Zhou, C. Zhang, F. Liu, Z. Qiu, and Y. He, "Application of deep learning in food: a review," *Comprehensive Reviews in Food Science and Food Safety*, vol. 18, no. 6, pp. 1793–1811, 2019, doi: 10.1111/1541-4337.12492.

[29] S. J. Chang and C. Y. Huang, "Deep learning model for the inspection of coffee bean defects," *Applied Sciences*, vol. 11, no. 17, 2021, doi: 10.3390/app11178226.

[30] N. F. Huang, D. L. Chou, and C. A. Lee, "Real-time classification of green coffee beans by using a convolutional neural network," *3rd International Conference on Imaging, Signal Processing and Communication*, pp. 107–111, 2019, doi: 10.1109/ICISPC.2019.8935644.

[31] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017, doi: 10.1145/3065386.
[32] C. S. Liang, Z. Y. Xu, J. Y. Zhou, C. M. Yang, and J. Y. Chen, "Automated detection of coffee bean defects using multi-deep learning models," *Proceedings - 2023 VTS Asia Pacific Wireless Communications Symposium*, 2023, doi: 10.1109/APWCS60142.2023.10234059.
[33] Y. Unal, Y. S. Taspinar, I. Cinar, R. Kursun, and M. Koklu, "Application of pre-trained deep convolutional neural networks for coffee beans species detection," *Food Analytical Methods*, vol. 15, no. 12, pp. 3232–3243, 2022, doi: 10.1007/s12161-022-02362-8.
[34] D. Buonocore, M. Carratù, and M. Lamberti, "Classification of coffee bean varieties based on a deep learning approach," *18th IMEKO TC10 Conference on Measurement for Diagnostic, Optimisation and Control to Saupport Sustainability and Resilience*, pp. 14–19, 2022, doi: 10.21014/tc10-2022.002.
[35] P. Wang, H. W. Tseng, T. C. Chen, and C. H. Hsia, "Deep convolutional neural network for coffee bean inspection," *Sensors and Materials*, vol. 33, no. 7, pp. 2299–2310, 2021, doi: 10.18494/SAM.2021.3277.
[36] K. Przybył *et al.*, "Application of machine learning to assess the quality of food products—case study: coffee bean," *Applied Sciences*, vol. 13, no. 19, 2023, doi: 10.3390/app131910786.
[37] T. Micaraseth, K. Pornpipatsakul, R. Chancharoen, and G. Phanomchoeng, "Coffee bean inspection machine with deep learning classification," *International Conference on Electrical, Computer, Communications and Mechatronics Engineering*, 2022, doi: 10.1109/ICECCME55909.2022.9987835.
[38] S. Y. Chen, M. F. Chiu, and X. W. Zou, "Real-time defect inspection of green coffee beans using NIR snapshot hyperspectral imaging," *Computers and Electronics in Agriculture*, vol. 197, 2022, doi: 10.1016/j.compag.2022.106970.
[39] C. Pinto, J. Furukawa, H. Fukai, and S. Tamura, "Classification of green coffee bean images basec on defect types using convolutional neural network (CNN)," *Proceedings - 2017 International Conference on Advanced Informatics: Concepts, Theory and Applications*, pp. 1–5, 2017, doi: 10.1109/ICAICTA.2017.8090980.
[40] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, and D. Anguelov, "Going deeper with convolutions," *2015 IEEE Conference on Computer Vision and Pattern Recognition*, vol. 40, no. 1, pp. 1–9, 2015, doi: 10.1109/CVPR.2015.7298594.
[41] V. Kurama and S. Mukherjee, "Deep learning architectures explained: ResNet, InceptionV3, SqueezeNet," *digitalocean.com*, 2020.

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