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Convolutional Neural Network-Based Ground Coffee Bean Classification in the Philippines

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ABSTRACT

While existing classification methods rely primarily on visual inspection or limited technological approaches, this research introduced a Convolutional Neural Network model specifically designed to address the challenges of classifying four major coffee varieties found in the Philippines: Arabica, Excelsa, Liberica, and Robusta. A comprehensive dataset of 1,817 ground coffee bean images captured in different lighting conditions, background colors, camera angles, and elevations was collected. To mitigate these challenges, advanced preprocessing and augmentation techniques were employed, including strategic resizing, flipping, and normalization to enhance the model's generalizability. The dataset was strategically divided into 80% training, 10% validation, and 10% testing sets to ensure efficient model performance. Utilizing TensorFlow and Keras on Kaggle, the CNN model was developed and subsequently deployed via a web-based application using Flask and HTML, offering an innovative, user-friendly interface for coffee bean classification. The model achieved a high overall classification accuracy of 96%, with Robusta and Arabica varieties demonstrating perfect classification. Thus, CNNs can effectively support the Philippine coffee industry by automating bean classification. Future work may focus on expanding the dataset to capture greater variability, refining the model—particularly for

Excelsa and Liberica varieties, exploring advanced machine learning techniques to improve consistency and real-world deployment, and integrating the model into real-time classification systems to support broader adoption in the coffee industry.

Keywords: *Convolutional Neural Network, deep learning, dataset augmentation, image classification model, coffee bean classification*

Introduction

As a cornerstone of economic development and national identity, the Philippine coffee industry represents more than just an agricultural sector—it embodies the cultural legacy and economic potential of the country's rich agricultural traditions. According to a study by Rocchetti et al. (2020), Coffea arabica and Coffea canephora (robusta) are the most extensively cultivated varieties of coffee (Coffea sp.), accounting for roughly 57% and 43% of the world's total production. While coffee has become a primary export and national beverage (World Coffee Research, 2022), accurate identification of local coffee bean varieties remains a critical challenge, particularly when beans are ground into a fine powder.

Existing coffee bean classification methods predominantly rely on manual visual inspection or traditional spectroscopic techniques, which prove inadequate when confronting the complexities of ground coffee. Previous research has primarily focused on whole bean classification, overlooking the unique challenges presented by ground coffee varieties (Balbin et al., 2021). Convolutional Neural Networks (CNNs) offer a transformative solution to this limitation, providing unprecedented capability to extract and analyze intricate textural and chromatic features that become indistinguishable to human perception in ground form.

According to Aghdamifarl et al. (2023), both the acidity and caffeine content of coffee can be helpful in assessing its quality and categorization. Additionally, the caffeine content improves classification and modeling outcomes, and the samples' caffeine content can be calculated and modeled using GEP programming. In another study, Mendes et al. (2022) stated that since the production regions leave behind distinctive markers, it is possible to authenticate green Arabica coffee beans by FT-MIR after harvesting, providing a quick and secure method of origin certification. This means they successfully classified their coffee beans based on their geographical origin.

The unique advantage of CNNs lies in their deep learning architecture, which can detect subtle microstructural variations across different coffee bean varieties—even when traditional visual cues are obscured by grinding. Unlike conventional image processing techniques, CNNs can learn hierarchical feature representations, enabling precise classification of Arabica, Excelsa, Liberica/Barako, and Robusta varieties found in the Philippines (Albawi et al., 2017).

In addition, Santos et al. (2020) demonstrated that coffee beans can be identified and classified with remarkable accuracy (over 88%) using computer vision and machine learning algorithms. On the other hand, Huang et al. (2020) classified good and bad coffee beans using a convolutional neural network (CNN) model. The experiment achieved a false-positive rate (FPR) of 0.0441 and an overall identification accuracy of approximately 94.63%. Gómez et al. (2019) proposed a classification approach for cocoa beans using spectral signatures from visible and near-infrared spectral bands. They categorized the cocoa beans into two groups: well-fermented and over-fermented. The research involved acquiring multispectral images of 64 grains, with 11 spectral images ranging from 350 nm to 950 nm per grain. Likewise, Khattak et al. (2021) developed an automatic detection system for citrus fruits using CNN, comparing its performance with support vector machine (SVM) and k-nearest neighbors (KNN) models. The CNN model emerged as the most effective, achieving an accuracy of 94.55%. However, the researchers acknowledged the potential for improvement, given the limited dataset of 213 images. Mihailova et al. (2022) demonstrated that the VideometerLab 4 system, combined with Orthogonal Partial Least Squares Discriminant Analysis (OPLS-DA), is a promising analytical tool for distinguishing roasted Arabica from Robusta coffee beans. By analyzing morphological, color, and spectral features, the study achieved 100% correct classification in the test dataset, highlighting the system's potential for rapid and non-destructive authentication of coffee species. Furthermore, Pradana-Lopez et al. (2021) developed a method capable of detecting adulterated coffee blends with an accuracy of 98.6% across 60 distinct groups. By integrating optical images with deep learning models, they created a user-friendly and cost-effective tool for coffee quality control.

Thus, this research addresses a significant technological and industrial gap by developing an innovative CNN model specifically designed to overcome the challenges of ground coffee bean identification. The proposed approach aimed to collect and preprocess a comprehensive dataset of ground coffee bean images representing regional Philippine varieties, develop an efficient Convolutional Neural Network model capable of accurately identifying and classifying these varieties, and integrate the model into an accessible web-based application to support industry stakeholders.

By using advanced deep learning techniques, this study sought to enhance quality control processes, support sustainable agricultural practices, and contribute to the Philippine coffee industry's global competitiveness. The research represents a critical step towards technological innovation in agricultural classification, offering a precise, efficient solution to a longstanding industry challenge.

Methods

Data Gathering

The research employed a quantitative methodology using Convolutional Neural Networks to address the challenge of identifying ground coffee bean varieties in the Philippine context. Recognizing the potential limitations of manually captured images, the researchers developed a comprehensive data collection strategy to maximize dataset diversity and model generalizability.

The primary research instruments included phone cameras for image capture, computational hardware for model training, and software tools for image processing and machine learning. Roboflow was employed for data augmentation and preprocessing, while Python-based machine learning libraries, including TensorFlow and Keras, were the primary tools for developing the CNN model.

The data collection procedure involved a systematic approach to gathering coffee bean images. The researchers manually photographed four distinct coffee bean varieties (Liberica, Robusta, Arabica, and Excelsa) under controlled conditions. Image capture considers multiple variables, including lighting conditions, background colors, camera angles, and elevations. This comprehensive approach ensured a diverse and representative dataset that could effectively train the machine learning model.

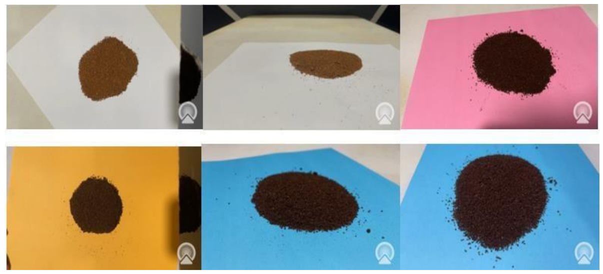

Figure 1. *Sample Images Taken by the Researchers*

Data Processing

This phase centers on preparing the dataset for effective machine learning by applying various preprocessing techniques. These processes enhance data quality, ensure consistency, and improve the model's ability to learn and generalize. Key steps in this phase include transforming the raw data, expanding the dataset through augmentation, splitting it into subsets for training, validation, and testing, and normalizing the data for efficient model processing.

To address the inherent limitations of manually captured images and enhance model effectiveness, a comprehensive preprocessing and augmentation strategy was implemented, such as auto-orienting, resizing, horizontal and vertical flipping, rotation (±15 degrees), random cropping, and slight shearing. These techniques artificially expanded the dataset and introduced variability, helping the model generalize across different imaging conditions and reducing overfitting risks.

Data Splitting

Dividing the dataset into distinct subsets is a critical methodological step in machine learning. The researchers strategically allocated their data into three segments: 80% for training the model, 10% for validation to fine-tune hyperparameters, and 10% for testing model performance. This careful partitioning ensures that the model can learn effectively, prevent overfitting, and accurately generalize to unseen data.

Data Augmentation

The augmentation process involves using existing data to expand the dataset. This helps the model become more efficient at variations in input data, reducing the risk of overfitting. As a result, despite various influencing factors, it improves the accuracy of classifying ground coffee beans in real-world conditions—auto-orienting, resizing, flipping, rotating, cropping, and shearing for data augmentation. To improve the model's effectiveness and allow it to generalize unseen data better, the ImageDataGenerator from TensorFlow's Keras API was employed. This function performs real-time data augmentation, which artificially enlarges the training dataset by generating modified versions of images. The validation dataset undergoes only rescaling to maintain the integrity of the evaluation metric.

Data Normalization

Data normalization refers to resizing image data to a consistent scale, enhancing the performance of machine learning models. In this study, all images were resized to 150 by 150 pixels to maintain uniformity. Additionally, pixel values were scaled to a range between 0 and 1, allowing the neural network to process the input data more efficiently.

Model Training and Testing

At this stage, the CNN architecture is constructed to build an accurate model for classifying ground coffee beans into four distinct categories defined in the dataset. In this phase, the CNN-based classification system was trained to accurately identify and classify different types of ground coffee beans. The model was optimized using the Adam optimizer and categorical cross-entropy loss function, suitable for multi-class classification problems. With the Adam optimizer’s default learning rate of 0.001, it provided a good balance between convergence speed and training stability. A batch size of 32 was used to optimize GPU memory usage while maintaining efficient training. These hyperparameter values were selected based on commonly recommended defaults in the literature and initial experimentation, which showed that they led to stable training and high model accuracy. The model was trained for 50 epochs, and training progress was monitored using accuracy and loss metrics on both the training and validation datasets.

Model Configuration

The CNN architecture was meticulously designed to tackle multi-class image classification of coffee bean varieties. The network's structure begins with an input layer accepting 150x150 pixel RGB images, followed by a strategic arrangement of convolutional layers with progressively increasing filter sizes (32, 64, and 128), each enhanced by ReLU activation functions and max-pooling layers to extract critical visual features. After compressing the spatial information, the feature maps are flattened and processed through a dense layer with 512 neurons, enabling the model to learn complex patterns. The final output layer, comprising four neurons with softmax activation, facilitates classification across the four coffee bean varieties. Compiled using the Adam optimizer and categorical cross-entropy loss function, the model was primed to deliver precise image classification with accuracy as the primary performance metric.

$$f(x) = \max(0,x)$$

Equation 1. *ReLU Formula*

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Equation 2. *Softmax Formula*

$$CE = -log\left(\frac{e^{s_p}}{\sum_{j}^{C} e^{s_j}}\right)$$

Equation 3. *Categorical Cross-Entropy Loss Formula*

Model Evaluation and Deployment

This marks the concluding phase of the study, where the performance of the refined CNN model was assessed. The model evaluation phase is dedicated to analyzing the performance of the CNN-based coffee bean classification model using the test dataset. The test images were preprocessed using the same pipeline applied during training, and predictions were made using the trained model. This stage helps determine the model's generalization ability and effectiveness in classifying various types of ground coffee beans in a real-world context. The CNN-based classification system is trained to accurately identify and classify different types of ground coffee beans. The model's performance was evaluated in terms of accuracy on both training and validation datasets. The model was trained over 50 epochs, and both training and validation performance were monitored. The number of steps per epoch was determined based on the number of samples and batch size. Once the model demonstrated satisfactory accuracy, it would be deployed in a web-based application to enable users to easily identify the four different types of ground coffee beans. To evaluate the model's classification accuracy, a confusion matrix was used to present both correct and incorrect predictions. Figure 4 illustrates the confusion matrix generated by the researchers using the validation dataset.

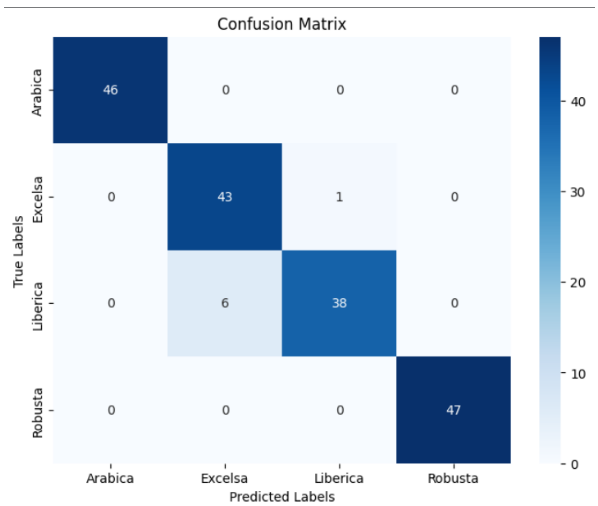

Figure 2. *Confusion Matrix*

Accuracy

Accuracy is a measure of how often a model makes correct predictions overall. Accuracy is determined by dividing the total number of correct predictions (both true positives and true negatives) by the overall number of predictions generated by the model. This metric works well when the dataset has an even balance of classes, but can be misleading when one class dominates. To monitor the learning behavior throughout the training phase, training and validation accuracy and loss values are plotted over the number of epochs. These plots help in identifying overfitting or underfitting tendencies and provide a visual summary of the model's learning progress. After training, the model was evaluated using the test dataset to determine its classification accuracy. This step verifies how well the model performs on data it hasn't seen during training. A confusion matrix was used to visualize the number of correct and incorrect predictions across all categories. It provides an intuitive overview of how well the model distinguishes between different ground coffee bean classes. A confusion matrix presents both correct and incorrect predictions to evaluate the model's classification accuracy.

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

Equation 4. *Accuracy Formula*

Precision

Precision quantifies the model's accuracy by measuring the proportion of predicted positive classifications that are correct, revealing how reliably the model identifies true positive instances. Precision becomes especially important in situations where false positives are costly.

$$\text{Precision}=\frac{TP}{TP + FP}$$

Equation 5. *Precision Formula*

Recall

Recall evaluates the model's ability to correctly identify all relevant instances, measuring the proportion of actual positive cases that were successfully detected.

$$\text{Recall}=\frac{TP}{TP + FN}$$

Equation 6. *Recall Formula*

System Design

To make the design process more manageable, simple low-fidelity wireframes for the web application pages were created. The researchers developed the application's wireframe using Figma.

In the implementation phase, the researchers used Visual Studio Code as the code editor, visual layout editor, and debugging tool to test the ground coffee bean web-based application on both virtual and physical devices. For the user interface, they employed HTML, while Python was used for the application's functionality. Additionally, Flask was utilized as their library.

In the development stage, the software was developed through coding, testing, debugging, and continuous refinement until it became fully operational and met the defined requirements. Assessing the model's accuracy was essential to ensure it can correctly classify images of ground coffee beans taken from the mobile device's image gallery.

Ethical Considerations

The exploration of coffee bean classification through Convolutional Neural Networks (CNNs) unveils a complex landscape of technological and ethical challenges that demand different, thoughtful consideration. As machine learning techniques increasingly intersect with traditional agricultural practices, researchers must carefully navigate the potential societal implications of their technological innovations.

The potential economic impact of the technology presents significant ethical considerations. While the CNN model promises to enhance quality control and efficiency in the coffee industry, the researchers are aware of the potential unintended consequences for small-scale farmers. Consequently, the technology must be developed and implemented in a manner that supports, rather than displaces, local agricultural workers. This approach necessitates creating accessible, affordable solutions that empower farmers and eliminate additional barriers to entry, ensuring that technological advancement does not come at the expense of local livelihoods.

Transparency in model development emerges as another critical ethical dimension. The researchers have committed to open documentation of their methodology, explicitly including limitations and potential biases in the model. By candidly acknowledging the model's imperfections, particularly in the classification of Liberica and Excelsa beans, they demonstrate a robust commitment to scientific integrity and a dedication to continuous improvement. This transparent approach not only enhances the credibility of the research but also establishes a framework for ongoing refinement and critical evaluation.

The broader ethical implications of technological intervention in traditional agricultural practices demand careful consideration. The fundamental goal is not to replace human expertise but to enhance and support the rich traditional knowledge of coffee production. The web application was intentionally designed as a supportive tool that provides assistance and information, profoundly respecting the deep cultural and historical significance of coffee production in the Philippines. This approach recognizes technology as a complement to, rather than a replacement for, the understanding developed by generations of local farmers.

Moreover, environmental sustainability represents another crucial ethical consideration underlying the research. By improving classification accuracy and supporting more efficient coffee production, the technology potentially contributes to more sustainable agricultural practices. The potential benefits include reduced waste, more precise resource allocation, and enhanced support for the long-term viability of coffee farming in the region. This approach demonstrates how technological innovation can align with ecological and economic sustainability.

Ultimately, the ethical framework of this research extends far beyond mere technical considerations. It embodies a holistic approach that prioritizes human dignity, cultural respect, and sustainable development within the Philippine coffee industry. By carefully balancing technological innovation with social responsibility, the research sought to create a model of technological intervention that empowers rather than marginalizes and enhances rather than disrupts traditional agricultural practices.

Results and Discussion

In the training phase, the model.fit() function was applied using train_generator to train the model over 50 epochs. To monitor the model's performance and help prevent overfitting, test_generator was used as the validation data, allowing the model to be evaluated after each epoch. The steps_per_epoch and validation_steps parameters were configured to enhance the training efficiency while conserving memory. The structure of the CNN model is presented in Table 1.

Table 1. Custom CNN Model Architecture

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72,72, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
flatten (Flatten)	(None, 36992)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
flatten (Flatten)	(None, 36992)	0
dense (Dense)	(None, 512)	18,940,416
dense_1 (Dense)	(None, 4)	2,052

After training, the model was evaluated using the test dataset to determine its classification accuracy. This step verified how well the model performs on data it has not seen during the training. A confusion matrix was used to visualize the number of correct and incorrect predictions across all categories. It provided an intuitive overview of how well the model distinguishes between different ground coffee bean classes.

Figure 2 illustrates the confusion matrix generated by the researchers using the validation dataset. This matrix summarizes the performance of the Convolutional Neural Network (CNN) model in classifying four ground coffee bean varieties: Arabica, Excelsa, Liberica, and Robusta. The matrix reveals that the model achieved perfect classification for both Arabica and Robusta, correctly identifying all 46 and 47 samples, respectively. This indicates that the model was highly effective in learning and distinguishing the unique visual patterns of these two varieties, even in their ground form. This suggests that the model can be effectively utilized for quality control processes involving these varieties. Accurate identification can aid in ensuring consistency in product quality, which is crucial for consumer satisfaction and brand reputation. Excelsa was also classified with high accuracy, with 43 out of 44 samples correctly predicted, and only one instance misclassified as Liberica. In contrast, the classification of Liberica showed some inconsistencies, with 38 correct predictions and 6 samples misclassified as Excelsa. This misclassification suggests a degree of visual similarity between ground Liberica and Excelsa beans, possibly due to overlapping features such as texture or color that remain after grinding. Misclassifications between these varieties could lead to issues in quality assurance, particularly if specific bean varieties are required for certain blends or products. This could affect the flavor profile and overall quality of the final product, potentially impacting customer satisfaction and market competitiveness.

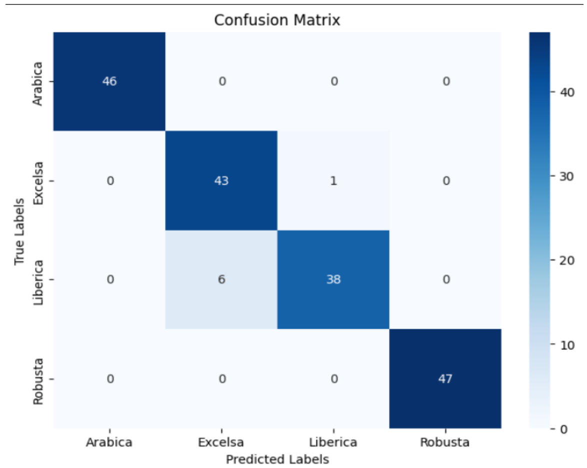

Figure 3. *Confusion Matrix*

The researchers sought to evaluate the model's performance by utilizing the matplotlib.pyplot library to generate visual representations of the training and validation accuracy, as well as the training and validation loss.

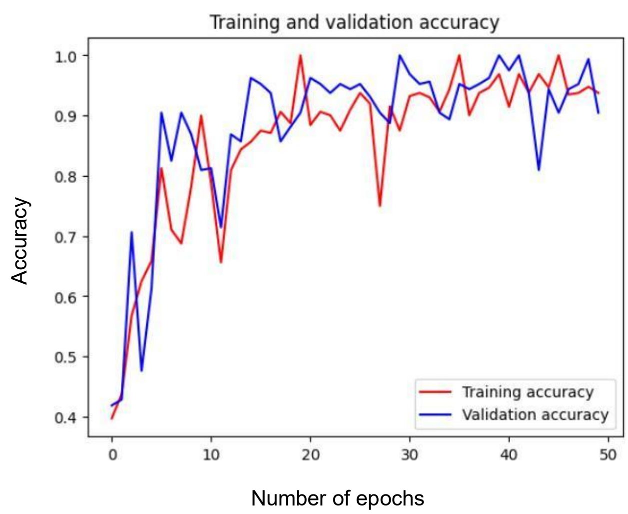

Figure 4. *Training and Validation Accuracy*

Figure 4 captures the training and validation accuracy progression of the machine learning model across 50 epochs. The accuracy curves demonstrate a consistent upward trajectory, with both training (red line) and validation (blue line) accuracies rapidly increasing during the initial training stages and then stabilizing around 90%. Despite slight fluctuations in the validation accuracy—a typical characteristic of models trained on varied datasets—the close alignment between the two curves suggests an effective generalization and minimal overfitting. By the final epoch, the model exhibits a strong, balanced performance across both training and validation datasets, indicating its effectiveness in learning and classifying coffee bean varieties.

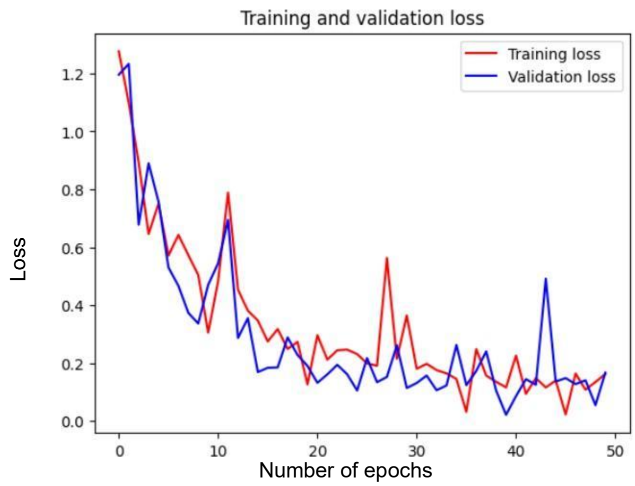

Figure 5. *Training and Validation Loss*

Figure 5 illustrates the training and validation loss progression of the machine learning model across 50 epochs, with the vertical axis representing loss values and the horizontal axis showing the number of training iterations.

During the initial training phases, the model's loss metrics for both training and validation datasets were elevated, with values exceeding 1.2. As the training progressed, both loss curves demonstrated a consistent downward trajectory, indicating the model's improving predictive capabilities and effective learning from the data. Approximately 10 epochs into the training, the loss values began to stabilize at lower levels, with the validation loss exhibiting occasional fluctuations—a typical phenomenon arising from the inherent variability in the validation dataset.

Despite these fluctuations, the overall downward trend in both curves demonstrates that the model was successfully minimizing error on both the training and validation sets. The similarity between the two curves also indicated that the model is not overfitting, as it maintains low loss on unseen validation data. By the 50th epoch, both losses converged to values close to zero, suggesting the model has achieved a high level of performance and generalization.

Table 2. Classification Report

	Precision	Recall	F1-score
Arabica	1.00	1.00	1.00
Excelsa	0.88	0.98	0.92
Liberica	0.97	0.86	0.92
Robusta	1.00	1.00	1.00
Accuracy		0.96	
Macro Average	0.96	0.96	0.96
Weighted Average	0.96	0.96	0.96

This classification report summarizes the performance of a model that classifies coffee bean types—Arabica, Excelsa, Liberica, and Robusta—based on key evaluation metrics: precision, recall, and F1-score.

The model's performance varied across different bean types. Arabica and Robusta demonstrated exceptional precision, with perfect classification scores of 1.00 for all metrics. Excelsa showed slightly less precision at 0.88, but maintained a high recall of 0.98, indicating nearly comprehensive identification of true Excelsa beans. Liberica exhibited high precision at 0.97, though its recall was lower at 0.86, suggesting the model was highly accurate in its Liberica predictions but occasionally missed some actual Liberica bean instances.

With an impressive 96% accuracy, the model demonstrated exceptional performance in classifying coffee bean varieties, consistently and precisely identifying samples across all categories. The macro and weighted averages of precision, recall, and F1-score, both at 0.96, underscore the model's balanced and reliable classification capabilities.

In summary, the model performs well, especially with Arabica and Robusta, and maintains strong, reliable results across all categories with only minor room for improvement in recognizing Excelsa and Liberica.

The identification and classification of coffee bean varieties is a crucial task for the coffee industry, as it supports quality control, sustainable practices, and overall efficiency. The researchers' study and their focal paper have explored different approaches to this challenge, each providing valuable insights.

The researchers approached the problem of coffee bean classification from different perspectives. This study focused on using a Convolutional Neural Network (CNN) model to accurately identify four local ground coffee bean varieties in the Philippines: Liberica, Robusta, Arabica, and Excelsa. The researchers collected a comprehensive dataset of ground coffee bean images, preprocessed, and augmented the data, and then developed a CNN model to classify the bean varieties.

In contrast, the focal paper titled "Classification of Coffee Variety using Electronic Nose" explored the use of an electronic nose device and statistical methods to classify coffee bean varieties (Delmo et al., 2022). The researchers in this study used an electronic nose with four different sensors to detect the gas data from coffee bean samples. They then performed correlation analysis on the sensor data to identify the potential of the electronic nose system in sensing the aroma of different coffee varieties.

While both studies aimed to classify coffee bean varieties, the approaches differed significantly. This study utilized advanced deep learning techniques, namely CNNs, to achieve high classification accuracy, while the focal paper relies on simpler statistical methods and an electronic nose device. It focused on ground coffee beans, which is a more challenging task than the whole bean classification addressed in the focal paper.

Additionally, the scope of the studies differs, with the researchers focusing on the Philippine coffee industry and the four local varieties, while the focal paper did not specify a geographical region or particular coffee varieties. This study also integrated its model into a web-based application, providing a practical solution for users, while the focal paper did not mention any application integration.

Overall, the two studies presented complementary approaches to coffee bean classification, with the researchers' study using the power of deep learning and the focal paper exploring the potential of electronic nose technology. Both studies contribute valuable insights to the field of coffee bean identification and quality control.

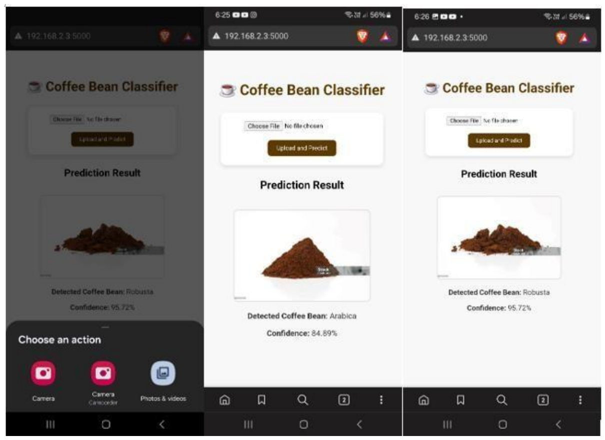

Figure 6. *Application User Interface with Classification*

The left part of Figure 6 shows the user the option to choose an image from their phone's gallery to upload and let the app predict. The middle part of the figure is a prediction of an uploaded image by the user. The app predicted that the ground coffee bean in the image is Arabica with a confidence rating of 84.89%. On the other hand, the right part of Figure 6 is a different uploaded picture of a ground coffee bean that is predicted to be Robusta with a confidence rating of 95.72%.

Conclusion and Future Works

This research developed a Convolutional Neural Network (CNN) model for classifying ground coffee bean varieties in the Philippines, achieving a notable 96% overall classification accuracy. By identifying and distinguishing four regional coffee bean varieties—Liberica, Robusta, Arabica, and Excelsa—the study demonstrated the potential of deep learning techniques in agricultural technology. The model showed particularly strong performance with Robusta and Arabica varieties, achieving perfect classification metrics.

While promising, the research acknowledges several limitations. The current dataset, though comprehensive, may not fully represent the extensive variability of coffee beans across different regions and processing conditions. Future research may focus on expanding the dataset, particularly for Liberica and Excelsa varieties, which showed less consistent classification results.

Furthermore, the key areas for improvement include expanding the dataset by collecting more diverse images capturing regional and processing variations, refining the model by exploring advanced CNN architectures such as MobileNet and EfficientNet—known for their lightweight structure and suitability for mobile deployment—and applying transfer learning with models like ResNet if a larger and more diverse dataset becomes available (Howard et al., 2017; Tan & Le, 2019). Further directions involve developing mobile-compatible platforms and potentially specialized imaging devices, as well as creating standardized classification protocols for small-scale producers. The study provides a foundational approach to applying machine learning in coffee bean classification, offering insights into how advanced technological methods can support agricultural quality control and potentially enhance efficiency in the Philippine coffee industry.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Artificial Intelligence (AI) Declaration Statement

The authors of this research acknowledge the use of Artificial Intelligence (AI) tools during the preparation of this manuscript. The authors hereby disclose the use of Artificial Intelligence (AI) tools during the preparation of this manuscript. AI-powered language assistance tools were utilized to help refine the clarity, grammar, and structure of our writing, particularly in drafting and editing sections of the paper. The AI tools used are JotBot AI Writing Assistant for manuscript drafting and editing, ChatGPT-4 for literature review assistance and technical writing refinement, and Grammarly AI for language editing and grammatical improvements. Additionally, AI tools were employed to assist in generating and debugging Python code for the Convolutional Neural Network (CNN) model, particualrly in implementing data preprocessing, model architecture, and training scripts. While these AI tools supported the research process, all substantive content, methodology, data analysis, and conclusions remain the original work of the authors, who retain full responsibility for the accuracy, integrity, and originality of the research. This declaration aims to provide full transparency about the use of AI in their research workflow, acknowledging both the supportive role of AI tools and the primacy of human research and interpretation. The authors are committed to responsible and ethical use of AI technologies in scientific research.