

A mobile application based on object detection algorithm for classifying robusta coffee cherry ripeness

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Abstract: Accurate classification of coffee cherries based on ripeness is essential for enhancing the efficiency of harvesting and ensuring high-quality coffee production. Traditional manual sorting is labor-intensive and inconsistent, necessitating an automated solution. This study addresses the challenge by developing a mobile application that uses an object detection algorithm to classify *Coffea canephora* (Robusta) cherries into four ripeness categories: unripe, semi-ripe, ripe, and overripe. The application leverages a smartphone camera to capture images, which are then analyzed by a deep learning model trained on 1,200 annotated images, and classify coffee cherries in real-time. Model performance of the YOLOv5 computer vision was evaluated using a validation dataset (400 images) and a test dataset (400 images), ensuring balanced representation across ripeness levels. The application achieved an overall classification accuracy of 95.63%, with the highest accuracy for unripe cherries (98.50%), followed by semi-ripe (94.75%), ripe (94.75%), and overripe (94.50%) cherries. These results demonstrate the effectiveness of integrating mobile technology with object detection algorithm for field-based classification of coffee cherry ripeness. The developed application is potential for improving harvesting efficiency, optimizing quality control, and supporting decision-making in the coffee industry. Future work should focus on expanding the dataset, refining the classification model, and implementing the system in microcontrollers to enable an automatic sorting hardware, thereby reducing farmers' workload and providing a comprehensive solution for our local stakeholders in the Bukidnon areas.

Keywords: ripeness classification; YOLOv5; coffee cherries; robusta coffee

1. Introduction

Coffee is a staple beverage for the Filipinos. In 2018, Ernie Masceron, the Senior Vice President and Head of Corporate Affairs of Nestlé Philippines, claimed that Filipinos are coffee lovers. Over 21 million cups of coffee are consumed daily in the Philippines [1]. The Filipinos consume as much coffee products as nations like the United States, Japan, Brazil and the European Union making it the 5th biggest coffee consumer worldwide [2]. In fact, coffee consumption in the Philippines has increased from 2009 to 2019 by 6.82% [3]. Additionally, according to a graph from Statista in 2022, coffee consumption in the Philippines has increased over the years. From 2.8 million 60kg bags of coffee in 2014, it increased to 3.31 million 60kg bags of coffee in 2020. The increasing demands of coffee products in the Philippines from 2014-2020 is shown in Figure 1.a. However, Filipino coffee farmers cannot keep up with the rising demands of coffee products in the country. This leads to importing at a steady volume of 100- 135,000 metric tons that costs the country about P7 Billion [4]. As shown in Figure 2, the coffee production in the Philippines decreased from an average of 127,412 metric tons in 1995 to only 60,044 metric tons of coffee products in the year 2019 (Figure 1.b).



Figure 1. (a) The increasing coffee consumption in the Philippines from 2014 to 2020 and (b) Coffee production in the Philippines from mid-1990s to 2019

Table 1 compares the production volume to the consumption of coffee products in the Philippines in the year 2020. According to statistical data from Figure 1, Filipinos consumed 3.31 million 60kg bags of coffee in 2020. On the other hand, the United States Department of Agriculture claimed that the Philippines only produced about 450,000 60kg bags of coffee products of the same year. This only shows that the country can only keep up about 14% of coffee demands in 2020. Additionally, the country is still 32.40% self-sufficient in coffee production, thereby making it 67.60% dependent on coffee products [5].

Table 1. The coffee industry in the Philippines in 2020

Production	Consumption
450,000 60KG Bags	3.31 million 60KG Bags

The unfortunate reality of the Philippine Coffee Industry is concerning since the country belongs to the Coffee Belt (Figure 2), an imaginary band around the equator where most, if not all, major coffee producing countries like Brazil, Vietnam and Indonesia falls into. Even though the Philippines' geographical location and features, climate, and soil condition makes it perfect for plantation of all four varieties of commercially viable coffee: Arabica, Liberica, Excelsa, and Robusta, Filipino farmers are still hesitant to invest in coffee industry because of its time-consuming and labor-intensive harvesting and processing. According to an article from the Philippines Coffee Board, Inc. picking only red ripe coffee cherries is a critical factor in producing high quality coffee beans. Picking immature cherries results in a more acidic and bitter flavor profile. While picking overripe coffee cherries can lead to off-flavors, mold, and other defects in the coffee [6]. Both instances can lead to poor coffee quality and lower yield.

Moreover, according to local coffee farmers in Bukidnon, despite many years of coffee cultivation, they still do not have access to any advanced technology or devices that help them in accurately categorizing coffee cherries based on their levels of maturity [7]. Although there are previous studies that aid in determining the maturity levels of coffee cherries, they do not employ real-time and offline detection and classification. Although this country, especially in rural areas, still lacks reliable internet connections. This needs to be considered in the development of assistive technology for local coffee farmers. With this, the challenge now is to make the Philippines a self-sufficient coffee producing country. With the help of technological advancements, research and innovations, it will hopefully be

able to assist local coffee farmers practice optimal coffee farming and processing techniques making it more economic and sustainable [8].

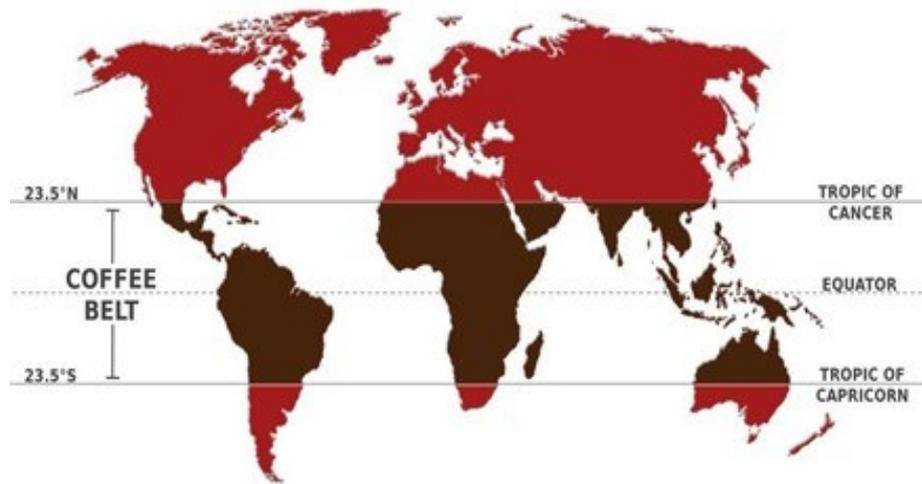


Figure 2. The coffee belt map [9]

Coffee cherries can be hand-picked by people to ensure that only the ripe cherries are picked, or they can practice strip-picking where the cherries are stripped off the branch which is not recommended. Hand-picking coffee cherry requires thorough inspection for maturity, which is a difficult and labor-intensive operation that, naturally, involves paid labor. Coffee cherries mature at various times, and it can take up to three pickings to clean out an entire farm. Picking ripe coffee cherries is very crucial in determining the quality of the coffee. Immature cherry harvesting in coffee production is associated with caustic, monotonous, or astringent sensory qualities [10]. When cherries are picked when they are ripe, they make a cup of coffee with a clean floral tea-like clarity, like jasmine or hibiscus, with a slight sweetness, like raw honey or sugar cane juice. Furthermore, research has indicated that beans from green-cane maturity stage coffee berries have lower dry matter and yield than completely ripe cherry fruits [11], [12]. Additionally, according to K.C. O'Keefe's Quality Formula, 35% of the coffee's quality is determined by the maturity of the cherries harvested. Therefore, the harvesting process is the most important variable among the other procedures in coffee production.

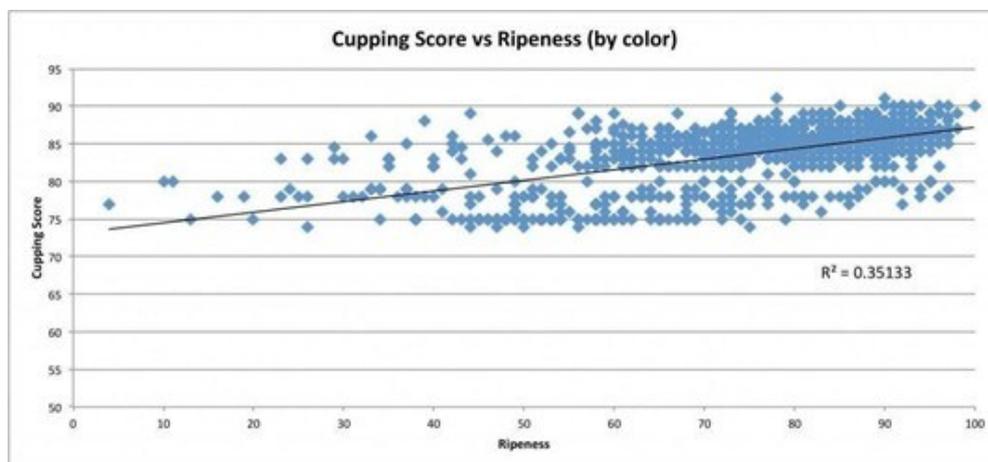


Figure 3. The relationship between cupping scores and ripeness level based on color [13]

The most common way to judge ripeness is through the color of the cherries. In fact, farmers from Cafe Pacas conducted a study where they compared the color of the 1000-day lots to their cupping scores and they found a strong correlation. Notice how cupping scores and ripeness, considering only the color, of coffee cherries correlates in Figure 3. The experiment they conducted proves the O'Keefe's Quality Formula.

Table 2. Summary of related studies

Image Acquisition	Detection and classification	Performance criteria	Result	Gap/remarks	Ref.
300 training images with solid white background	Image processing HSV color KNN method	Ratio of total correct data from total test data (in %)	95.56%	1) Uses the traditional identification and classification method 2) Only 3 classifications of ripeness (unripe, ripe, half ripe) 3) Non-real time classification	[14]
Frames derived from videos	Yolov3-tiny Algorithm	Precision, recall, F1-score average precision (mAP)	mAP: 84%	1) Only 3 classifications of ripeness (unripe, ripe, overripe) 2) Used an older version of YOLO with less accuracy rate	[15]
4000 raw images captured from a smartphone camera 5MP resolution	Convolutional Neural Network	Confusion Matrix	98.75%	1) non-real time classification 2) used a deep learning algorithm that is not suitable for mobile phones	[16]
Frames from the mobile application camera	You only Look Once version 5 (YOLOv5)	Confusion Matrix, Precision Recall, Specificity, F1-score. Missed Detection, False Detection, AP, mAP, Accuracy	-	1) Real-time identification and classification 2) Uses four classifications of coffee fruit maturity levels: unripe, semi-ripe, ripe and overripe 3) Used a more improved and accurate version of Yolo algorithm	Proposed study

The following related studies presented above utilize different methods in detecting and classifying coffee cherries as provided in Table 2. Moreover, the researcher included the proposed methods in identifying and classifying coffee cherries.

This study aims to develop a mobile application capable of object detection and classification that can accurately classify coffee cherries according to their maturity levels. Moreover, the researcher aims to develop a mobile application that is capable of real-time detection and accurate classification of unripe, semi-ripe, ripe, overripe coffee cherries based on the samples provided by a local Robusta coffee farm with the use of YOLOv5 object detection algorithm without the need for internet connectivity. The findings of this study can benefit the coffee farming industry since it provides technological advancement and aid in the coffee farming industry. The results of this study will aid the Filipino coffee farmers in systematizing the coffee cherry classification and sortation process. Furthermore, this solution serves as an assistive technology for new coffee farmers without experience, and in-depth knowledge and skills in classifying coffee cherries based on their ripeness level.

2. Material and methods

This study adopted the developmental research design which involves developing mobile applications, capable of image analysis for classifying unripe, semi-ripe, ripe and overripe Robusta coffee cherries, to accurately classify coffee cherries based on their maturity level using deep learning and object detection algorithm. The independent variable in the study is the input of the algorithm which are the images of coffee cherries acquired by utilizing the Huawei Nova 3i camera. On the other hand, the output is the labels that will appear on the smartphone's screen whether the detected coffee cherry within the bounding box is unripe, semi-ripe, ripe or overripe. The collection of training, validation and testing data (coffee cherry images) was conducted at local Robusta coffee farms located at Pangantucan and Lantapan, Bukidnon. This research locale is specifically chosen since Robusta Coffee Trees are available in the area. Also, the farmers are willing to accommodate the study and provide sorted Robusta coffee cherry samples.

The system receives a live feed from the camera, which consists of frames containing Robusta coffee cherries. These frames serve as the primary input data for further analysis and processing. Each frame represents a snapshot of the coffee cherries within the scene, forming the basis for subsequent steps. These digital frames undergo processing using the YOLOv5 object detection algorithm, renowned for its real-time object detection capabilities. This advanced deep learning-based model analyzes each frame, detecting and localizing the coffee cherries present within the image. Additionally, this process involves estimating the probability that an object is present in a cell, then calculating the object score, estimating the bounding box coordinates around the object based on the object score, and finally, estimating the classification of the object within the bounding box using the YOLOv5 algorithm. The algorithm's primary objective is to identify and classify the coffee cherries based on their ripeness levels.

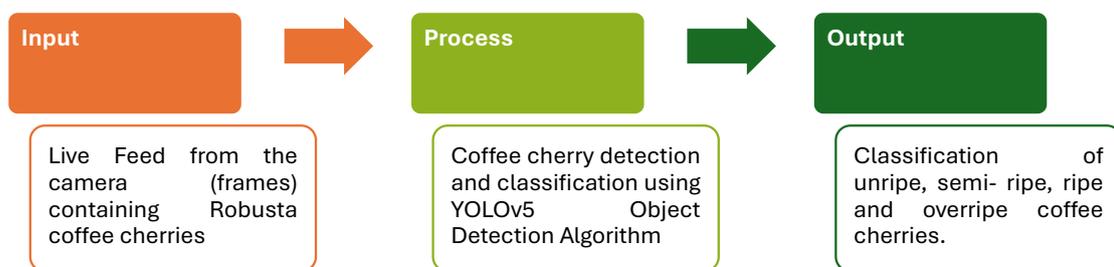


Figure 4. Research framework

The final output of the framework is the classification of the coffee cherries into distinct categories, including unripe, semi-ripe, ripe, and overripe. This classification is achieved through the examination of visual cues and patterns exhibited by the coffee cherries within the frames. By presenting a

conceptual framework through Figure 4, the study aims to provide a structured and systematic approach to analyzing the ripeness levels of coffee cherries.

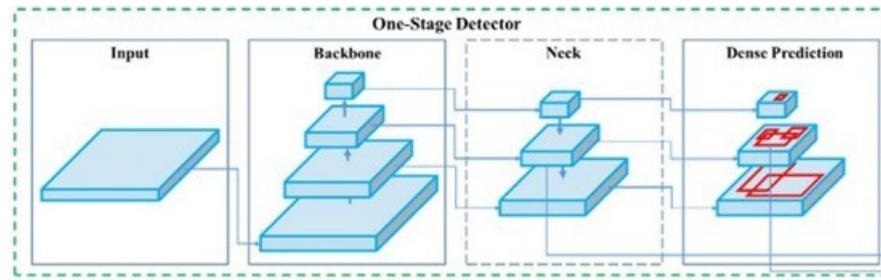


Figure 5. The relationship between cupping scores and ripeness level based on color

The researcher determined during the review of literature that existing similar studies had employed non-real-time object detection and image processing algorithms. Additionally, a similar study used the You Only Look Once version 3 (YOLOv3), an outdated version of YOLO object detection algorithm. In light of the aforementioned findings, the study will utilize the You Only Look Once version 5 (YOLOv5) for the training of custom dataset, which provides faster processing, improved accuracy for real-time object recognition, and best suited for low level GPUs in smartphone applications.

The backbone network is responsible for extracting features from the input image. This helps in reducing the image's spatial resolution and raising its feature (channel) resolution. While the neck network is responsible for combining features from different scales to create a single feature map that is used for object detection. This makes it easier for the model to generalize to objects of various sizes and scales. And the detection head is responsible for predicting bounding boxes and objectless scores for potential objects in the image.



Figure 6. System architecture of coffee cherry mobile application

Figure 6. shows the system architecture of the Robusta Coffee Cherry Ripeness Classification mobile application. The mobile app is designed to be user-friendly and straightforward. The swim lane diagram in Figure 8 serves as a visual tool used that illustrates the flow of activities and interactions between different entities of the training and testing phase of the YOLOv5 object detection model. It shows the different stages of the training process, such as data preparation, model configuration, model training, model evaluation, model tuning and model testing.

YOLOv5 is mainly an object detection algorithm, however it also employs several digital image processing in both its training and testing phases. Firstly, the training phase begins with the data preparation where signal processing techniques play a crucial role in optimizing the training data. Techniques such as image resizing and normalization are applied to ensure consistent input dimensions

and to scale the pixel values to a suitable range. These techniques leverage signal processing principles to modify the images while preserving their key characteristics, enabling the YOLOv5 model to learn from a more varied dataset. Consequently, the model configuration stage involves selecting and configuring the convolutional layers and defining the network architecture. The deep learning architecture that the YOLOv5 algorithm employs is the Convolutional Neural Network (CNN) which is specifically designed for image processing tasks and utilizes signal processing to extract hierarchical features from the input images.

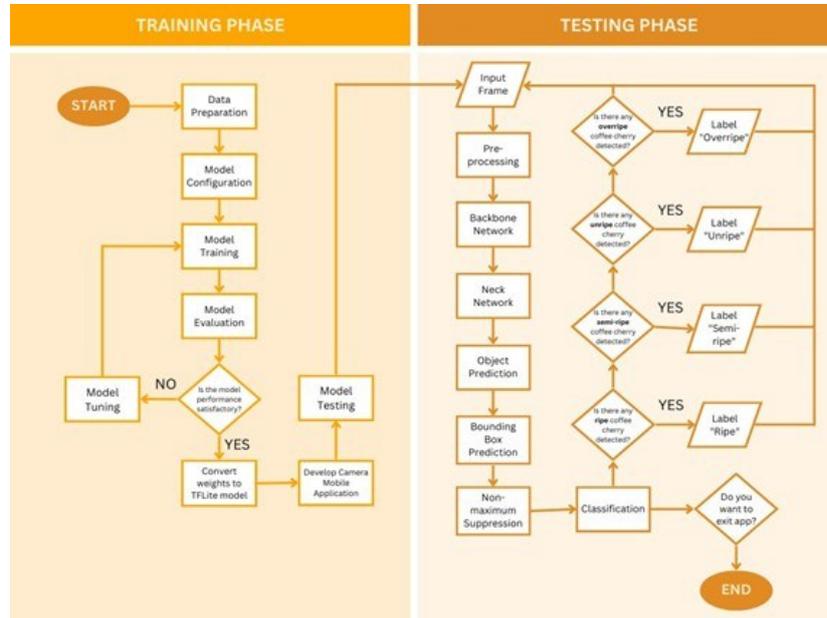
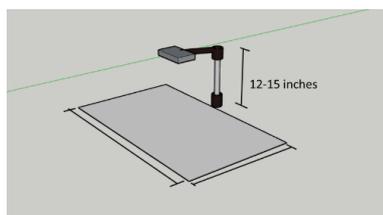


Figure 7. Swimlane diagram of the mobile application

Moreover, the testing phase begins with opening the working mobile application and start feeding input frames by detecting analog light signals and converting it into digital images. These images are then pre-processed which include operations such as image enhancement, noise reduction, or contrast adjustment. The backbone network in YOLOv5, typically a deep Convolutional Neural Network (CNN), is responsible for extracting features that represent various visual patterns and objects from the pre-processed frame. The neck network, an intermediate component in YOLOv5, further refines the features extracted by the backbone network. Feature fusion and feature aggregation are employed to combine information from multiple levels of the backbone network, enabling the model to capture both low-level and high-level features with enhanced contextual information. The neck network facilitates better feature representation and improves the detection performance of the model. Lastly, object prediction, bounding box prediction and non-maximum suppression all encompasses the detection head of YOLOv5 architecture.



(a)



(b)

Figure 8. (a) Experimental setup, and (b) Implementation

The implementation and testing of the coffee cherry mobile application was conducted in an indoor setup as shown in Figure 8. The phone is placed 12-15 inches above the surface. The surface can be a “nigo” which is mostly used by the local coffee farmers for sorting the coffee cherries. The first test is done through individual placement of coffee cherries into the “nigo” within the camera frame for detection. This is to determine the True Positives, False Positives, False Negatives, and True Negatives. With this gathered data, the researcher will be able to compute the Precision, Recall, AP, Specificity, F-1 Score, False Detection, Missed Detection, mAP, and Accuracy of the mobile application. The first test is done through individual placement of Robusta coffee cherries into the “nigo” to determine the number of True Positives, True Negatives, False Negatives and False Positives. The second test is done through placing several coffee cherries with different maturity levels into the “nigo” and capturing it in one frame. This is to test whether the Robusta Coffee Cherry Ripeness Classification mobile application is still performing accurately and consistently in three different trials: (1) 20 test objects, (2) 50 test objects, and (3) 100 test objects in one frame. Figure 10 shows sample testing and implementation of the first test.

3. Results and discussion

The researchers were able to develop a Coffee Cherry Ripeness Classification Mobile Application in Figure 9 that is capable of real-time detection and accurate classification of unripe, semi-ripe, ripe, overripe coffee cherries based on the samples provided by local Robusta coffee farms in Bukidnon with the use of YOLOv5 object detection algorithm without the need for internet connectivity.



Figure 9. Working robusta coffee cherry ripeness classification mobile application

The researchers were able to develop a Coffee Cherry Ripeness Classification Mobile Application in Figure 9 that is capable of real-time detection and accurate classification of unripe, semi-ripe, ripe, overripe coffee cherries based on the samples provided by local Robusta coffee farms in Bukidnon with the use of YOLOv5 object detection algorithm without the need for internet connectivity.

The experimental procedure of this study is composed of two different experimental test setups: (1) individual placement of Robusta coffee cherries to determine the number of true positives, false positives, and false negatives that will be used for data analysis, and (2) placing several Robusta coffee cherries in one frame. The latter consisted of test cases at different numbers of mixed-ripeness levels of Robusta coffee cherries in one frame (20 pieces, 50 pieces, 100 pieces). This test is essential to determine whether the proposed mobile application’s performance increases or decreases as the number of coffee cherries present in one frame increases.



Figure 10. Experimental procedure and data gathering

Figure 11 summarizes the performance of the YOLOv5 model by showing the number of correct and incorrect classifications made by the model on a validation dataset using a confusion matrix. A confusion matrix is a table that is commonly used in the evaluation of classification models. This confusion matrix is generated from the training phase of the algorithm. The rows represent the true class labels, while the columns represent the predicted class labels. To determine the correct classifications of the model, the diagonal cells of the matrix present the number of correct classifications. It is shown that all four classes of maturity levels (unripe, semi-ripe, ripe, overripe) have high numbers of True Positives. Consequently, “Unripe” has 93% correct classifications, “Semi-Ripe” has 96% correct classifications, “Ripe” has also 97% correct classifications, and lastly “Overripe” has 80% correct classifications. Overall, it is evident that the algorithm performs relatively well in predicting all four classes.

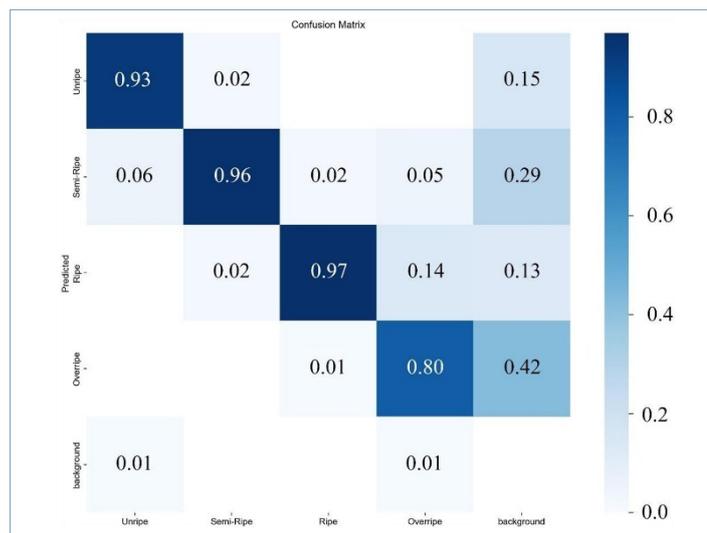


Figure 11. Performance of training phase

The confusion matrix in Table 3 shows the performance of the Robusta Coffee Cherry Ripeness Classification mobile application in classifying four different maturity levels of Robusta coffee cherries: Unripe, Semi-ripe, Ripe, Overripe. The rows represent the true labels, while the columns represent the predicted labels. From the confusion matrix, it shows that:

1. The proposed mobile app correctly classified 94 Unripe, 90 Semi-ripe, 92 Ripe, and 89 Overripe.

2. The proposed mobile app incorrectly classified 6 Unripe, 10 Semi-ripe, 8 Ripe and 11 Overripe.
3. The most misclassified maturity level was the Overripe, with 8 Overripe coffee cherries being incorrectly classified as Ripe, and 3 as Semi-ripe.
4. The highest True Positive count class of coffee cherry maturity level is “Unripe” with 94 correct classifications.

Table 3. Confusion matrix

		Predictions			
		Unripe	Semi-ripe	Ripe	Overripe
Labels	Unripe	94	6	0	0
	Semi-ripe	0	90	5	5
	Ripe	0	2	92	6
	Overripe	0	3	8	89

4. Conclusion

The Robusta Coffee Cherry Ripeness Classification mobile application developed in this study has shown promising results in accurately identifying and classifying coffee cherries' maturity levels in real-time without the need for internet connectivity. Robusta Coffee Cherry Ripeness classification mobile application's successful development opens new opportunities for improving efficiency, optimizing quality control, and facilitating decision-making processes in the coffee farming industry. However, there are limitations to this study that should be considered. Future work will include expanding the dataset, refining the classification model, and incorporating additional features such as implementing the Robusta Coffee Cherry Ripeness Classification model in microcontrollers to include an automatic sortation system, which will reduce coffee farmers' workload and increase the efficiency of the harvesting and sorting process.

Author's declaration

Author contribution

Natasha Marie D. Relampagos led the development of object detection algorithms, designed experimental framework for ripeness classification, and implemented mobile application architecture. **Kristine Mae P. Dunque** conceptualized the study, provided coffee cherry fruit sample collection, and administered the overall research process. Both authors contributed equally to the writing, review, and editing of the manuscript for publication entitled “*A mobile application for robusta coffee cherry ripeness classification using object detection algorithm*”.

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Data availability

The datasets collected and analyzed are not publicly available due to the ongoing improvement of the mobile application. However, detailed descriptions of the dataset composition are included in the manuscript.

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Conflict of interest

The authors declare no competing interests.

Ethical clearance

This research does not involve human as subjects.

AI statements

This article is the original work of the authors without using AI tools for writing sentences and/or creating/editing tables and figures in this manuscript.

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