Development of IoT Automated Color-based Sorting Machine for Robusta Coffee Cherries (*Coffea canephora*)

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Abstract

This research focused on creating an IoT-enabled color-sorting machine for Robusta coffee cherries, utilizing image processing as an effective alternative to manual sorting. The system tackles a significant issue with the strip-picking harvesting method, which gathers cherries at different ripeness levels, negatively affecting coffee quality. The machine sorts cherries by ripeness—red for ripe, green for unripe, and black for overripe—using a detection model trained through image processing and implemented on a Raspberry Pi 4 Model B. The performance was assessed based on sorting speed and classification accuracy. The detection model successfully identified 277 out of 300 cherries, resulting in an overall classification accuracy of 92.33% and a mean precision of 92.55%. In practical tests with 100 cherries over 10 trials, the machine achieved an average sorting accuracy of 86.83% and a mean sorting time of 21 minutes and 33 seconds. When compared to a previously developed coffee bean sorter, the new device showed improved accuracy and faster processing speed.

Keywords: Convolutional Neural Network, Image processing, Strip picking

Introduction

Coffee is among the top agricultural commodities traded internationally, experiencing a steady rise in demand (Voora, Bermudez, & Larrea, 2019). In the production of coffee, selecting ripe cherries and their variety is crucial, as proper harvesting and sorting are essential steps to achieve optimal quality. Fully ripe cherries exhibit a range of colors from light to shiny deep red, while unripe cherries appear green, yellow, or orange, and overripe cherries can be dark red to black (Coffee Behind the Scenes, 2018). Coffee cherries can be harvested either by machines or by hand, using two methods: strip picking or selective picking. Selective picking is labor-intensive, as it focuses on harvesting only the ripe red cherries, making it ideal for high-quality Arabica coffee (Caretti, 2016). In contrast, strip picking involves mechanically removing all cherries at once, which is quicker and requires less labor but can result in a mix of ripe and unripe fruits. To address this, pulpers and optical sorters are employed after harvesting (Koffee Kult, 2018). Several factors, including genetics, environmental conditions, nutrition, crop management, harvesting, and preparation, influence the physical and chemical properties of coffee (Haile & Hee Kang, 2019). A review by Howard (2011) highlights the strong connection between post-harvest processing methods and the levels of fructose and glucose in coffee beans, noting that differences in flavor can arise from variations in processing thoroughness. After harvesting, coffee cherries must be sorted to ensure that only those at optimal ripeness are selected, which is vital for achieving high-quality end products. However, manual sorting is a labor-intensive process that requires significant time, effort, and attention to detail (Stanley-Foreman, 2023).

The rise of automation in agricultural practices is becoming an increasingly important issue globally, especially as the world population continues to grow, leading to a constant demand for more food. Traditional farming methods, which many farmers still rely on, are struggling to meet this demand. A study by Jha, Doshi, Patel, and Shah (2019) highlighted successful examples of automation and wireless technology in agriculture, such as smart farming and robotics. Lowenberg-

DeBoer, Huang, Grigoriadis, and Blackmore (2020) noted that while there is a wealth of research on crop robotics, there is a lack of studies focusing on the economic aspects of this technology. In a chapter by Edan, Han, and Kondo (2009), it was mentioned that the adoption of automation in agriculture has resulted in lower production costs, reduced manual labor, enhanced quality of fresh produce, and better environmental management. A review by Mahmud, Abidin, Emmanuel, and Hasan (2020) found that cost is a key factor for farmers when considering investments, suggesting that the implementation of autonomous systems worldwide is feasible.

Currently, Internet of Things (IoT) technology focuses on connecting people to people, people to objects, and objects to objects (Russo, Marsigalia, Evangelista, Palmaccio, & Maggioni, 2015). IoT solutions can enhance agricultural productivity while reducing expenses (Sreekantha & Kavya, 2017). To address certain communication challenges, it is essential to create technology that consumes less energy and features user-friendly interfaces (Dhanaraju, Chenniappan, Ramalingam, Pazhanivelan, & Kaliaperumal, 2022). The primary aim of this study is to design an IoT-based sorting machine that categorizes coffee cherries harvested using the strip picking method according to their ripeness, as indicated by their colors: red, green, and black. To achieve this main goal, the specific objectives include building the chassis and circuitry of the sorting machine, training and implementing a detection algorithm using image processing, integrating an IoT-based monitoring and data collection system, and testing and assessing the sorting machine for accuracy and speed.

This study presents a novel IoT-enabled color-sorting machine specifically designed for Robusta coffee cherries, addressing a persistent challenge in post-harvest processing associated with the strip-picking technique, which results in a mix of cherries at different ripeness levels. The machine stands out due to its implementation of image processing algorithms on an affordable and compact Raspberry Pi 4 Model B platform, enabling it to classify cherries into three categories based on their color: ripe (red), unripe (green), and overripe (black). Unlike previous systems, this machine eliminates the need for manual sorting, offering a more reliable, scalable, and data-driven solution. It also demonstrates significant improvements in classification accuracy and sorting speed compared to earlier prototypes developed at the same institution. Furthermore, the incorporation of IoT features facilitates remote monitoring and the potential for integration with larger digital farm management systems, marking a significant advancement in automating quality control in coffee production.

Materials and Methods

Construction of the Machine Chassis

The sorting machine chassis consisted of a hopper where the coffee cherries were fed into, utilizing a spinning motion to release the cherries one at a time into the scanning chamber beneath. Every falling cherry is directed by two pipes, with the servo motor triggering the cherry's entry into the moving pipe upon detection, ensuring it lands in the correct pipe aimed at the right bin. The block diagram of the system is shown in Figure 1.

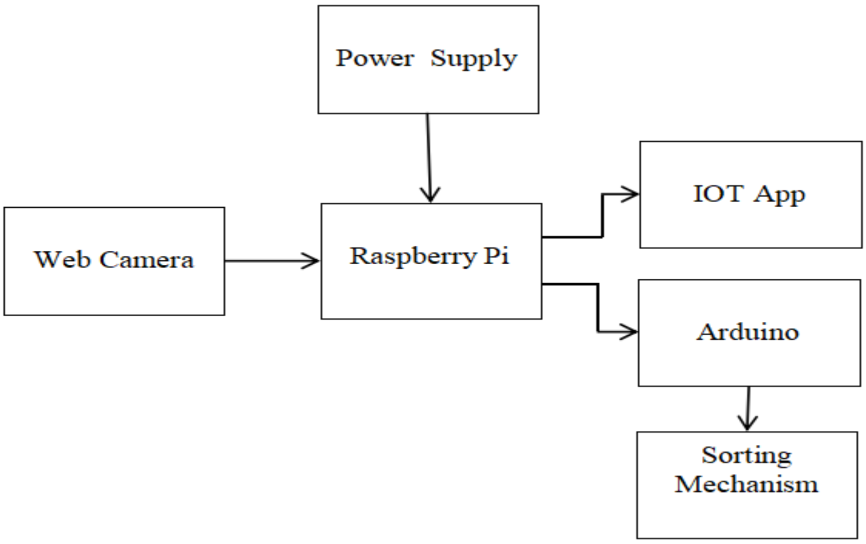


Fig. 1. Block diagram of the system

The components of the sorting machine are shown in Figure 2, including the microcontroller box, hopper, stepper motor, tube pipe, camera, rollers, moving hand, moving pipe, and the pipes leading to the bins. The dimensions of the design are also shown which is 80 × 35 × 75 centimeters. The machine can be opened for immediate troubleshooting. The X-ray view and top view of the machine are shown in Figure 3.

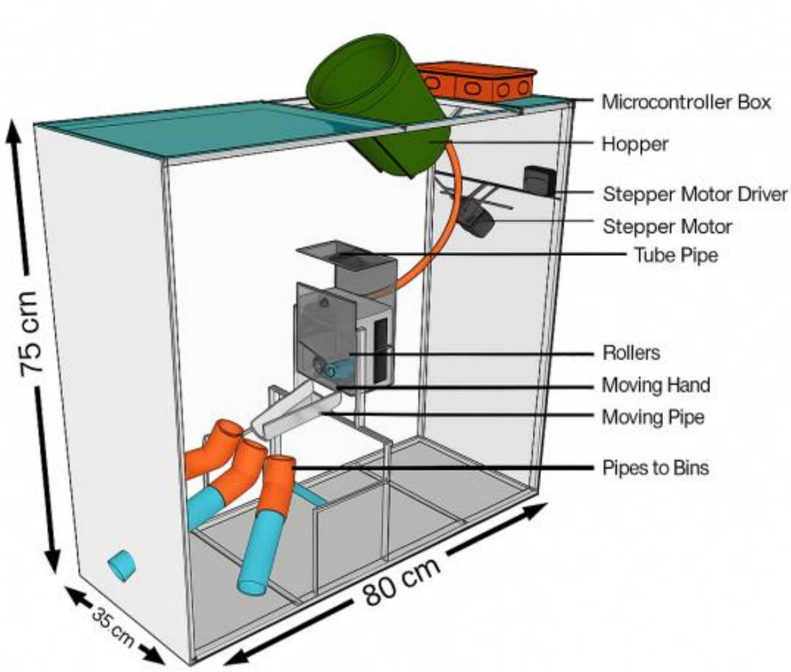


Fig. 2. Interior of the machine with labeled parts and dimensions

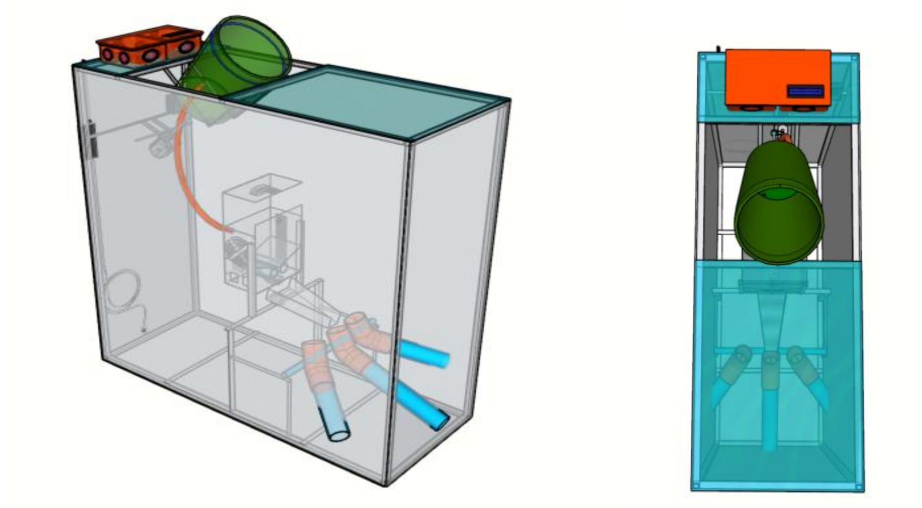


Fig. 3. X-ray view (left) and top view (right) of the machine

Construction of the Machine Circuitry

The wiring diagram of the entire system was shown in Figure 4. Two microcontrollers were used, which were the Raspberry Pi and Arduino UNO, but the main control unit was the former. The stepper motor was connected to the TB6600 stepper motor driver and was compatible with the Arduino UNO. There were two buck converters connected to the servo motors, the stepper motor driver, and the LED. The four servo motors, on the other hand, were directly connected to the Arduino UNO, while only the web camera and the Arduino UNO were directly connected to the Raspberry Pi. Each microcontroller is assigned its own dedicated power supply connection. The two microcontrollers communicate with each other through the devised program and act as the control units for both the color sorter and the motors.

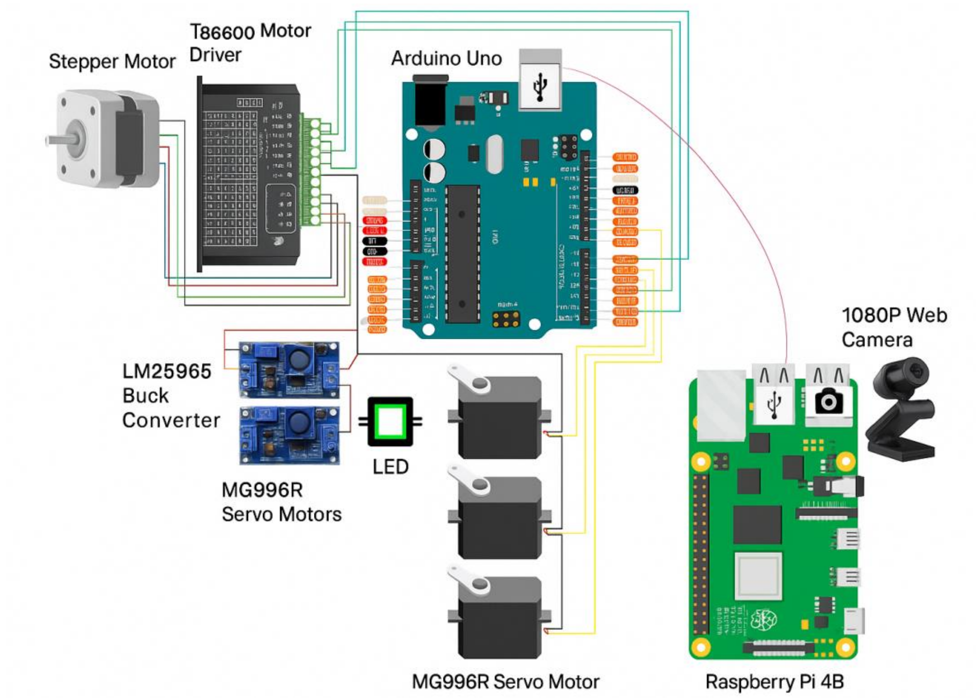


Fig. 4. Wiring diagram of the system

Implementation of the CNN Architecture

The structure of the CNN was created using the Python programming language, which includes certain libraries. Tajinder (2023) stated that CNN is a subclass of deep neural networks that are very good at handling tasks involving images since they are specifically made to process and evaluate visual data. Tripathi (2023) described the three types of layers in CNN, which are the Convolutional Layer, Pooling Layer, and Fully-Connected Layer.

The study utilizes the Single-shot Multibox Detector (SSD) MobileNetV2, a pre-trained CNN model known for its effectiveness in object detection. The pre-processed image dataset was trained using this model. Designed for mobile and embedded vision applications, MobileNet is a class of well-organized models based on a simplified architecture that builds lightweight deep neural networks using depth-separable convolutions. A study conducted by Howard *et al.* (2017) investigated some of the key design decisions contributing to an efficient model and proposed a model based on depth-wise separable convolutions, achieving remarkable improvements in size, speed, and accuracy. Meanwhile, the SSD method relies on a forward convolutional network to provide a set of fixed-size bounding boxes and a score for the existence of object class instances in those boxes. The final detections are then produced by a non-maximal suppression step.

Image Dataset for CNN and Image Preprocessing

The coffee cherry samples were purchased from several small farms located in General Emilio Aguinaldo, Cavite province, Philippines, and 1000 images of each ripeness level of coffee cherry were acquired: unripe, ripe, and overripe. A sample image illustrating each stage of the coffee cherry's ripeness is shown in Figure 5.

(a) (b) (c)

Fig. 5. Coffee cherry sample: (a) unripe, (b) ripe, and (c) overripe

To increase the range of dataset training, the researchers acquired an additional 2000 images of coffee cherry from Kaggle, which is a data science competition platform. A dataset of 5,000 coffee cherry images was used, which was segmented into the categories of unripe, ripe, and overripe. To prepare the dataset, all images were cropped to a 1:1 ratio and resized to 256×256 pixels for training consistency, since the images did not need much detail. The images were also manually labeled using LabelImg, which is a Python-based graphical image annotation tool.

IoT-based Ripeness Classifier System

In order to create the system of device classification, everything was programmed using the Python programming language with the use of all necessary libraries such as Keras and TensorFlow, which go hand in hand. The flowchart presented in Figure 6 outlines the classifier system, starting with the upload of the labeled image dataset to prepare for training using TensorFlow. The dataset has been organized into three separate folders: one for the raw images, another for training the algorithm, and the last reserved for the model's final testing phase. The webcam detects the coffee cherries in real time, classifies their ripeness level, and the process is displayed on the mobile app.

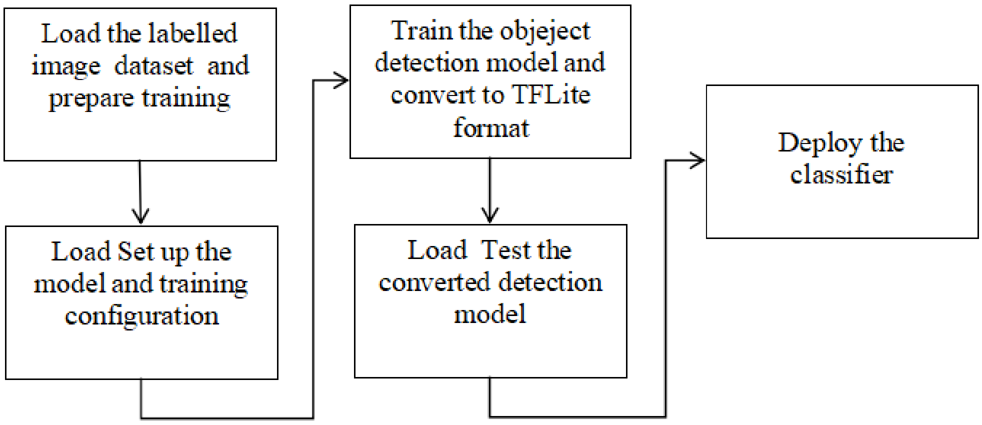


Fig. 6. Flowchart of the classifier system

Equations (1)-(3) were used to compute the accuracy per trial of each bin category, and the accuracy values shown in Table 3 are the average of those.

$$\text{GB Accuracy} = \frac{\text{GB content}}{\text{GB inputted sample}} - \frac{\text{RB content} + \text{BB content} + \text{Not sorted}}{\text{Total inputted samples}} \times 100 \qquad (1)$$

$$\text{RB Accuracy} = \frac{\text{RB content}}{\text{RB inputted sample}} - \frac{\text{GB content} + \text{BB content} + \text{Not sorted}}{\text{Total inputted samples}} \times 100 \qquad (2)$$

$$BB\ Accuracy = \frac{BB\ content}{BB\ inputted\ sample} - \frac{GB\ content + RB\ content + Not\ sorted}{Total\ inputted\ samples} \times 100 \qquad (3)$$

where, GB = green bin; RB = red bin; and BB = black bin

Android Mobile Application

The mobile app used to activate and deactivate the system was programmed using the Java programming language in an IDE called Android Studio. Figure 7 shows the flowchart of the app interface which is what is shown on Android phones, where the app can be installed and run.

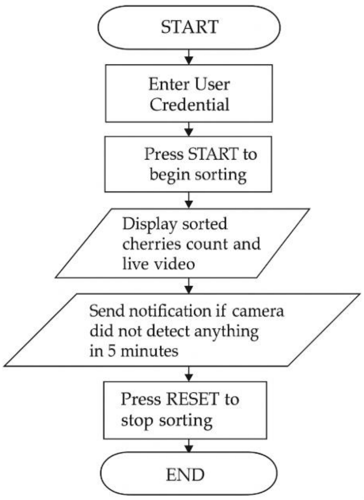


Fig. 7. Flowchart of the GUI

Results and Discussion

Chassis and GUI of the Device

The chassis of the prototype encloses all its main components except for the control unit, and it is covered with a hard plastic at the top that allows for easy inspection of the motors to ensure they are functioning correctly. The internal part of the device, as shown in Figure 8, consists of the camera, the scanning chamber which includes the moving hand and rollers, and the pipes. For the scanning chamber that has the smaller PVC pipes as rollers in it, hard plastic was used to create a box that encloses the motors needed there.

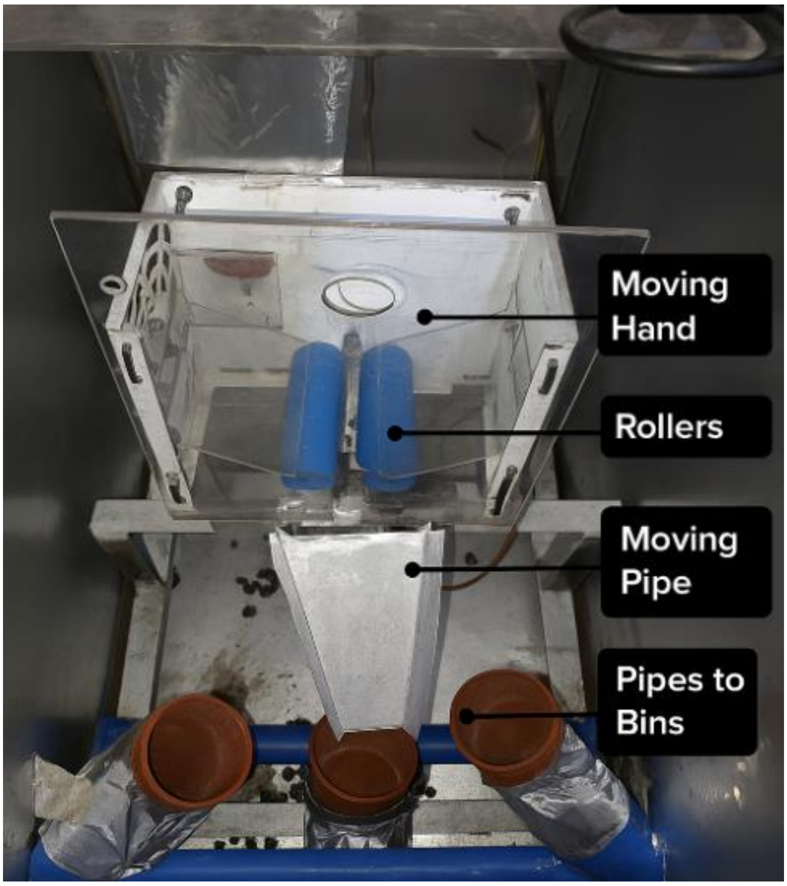


Fig. 8. Internal view of the device

Figure 9 illustrates the completed prototype, featuring a hopper designed for feeding coffee cherries. The lower section is constructed from a modified plastic basket, while the upper portion is crafted from galvanized plain sheet metal. It is 50 cm in circumference, 40 cm in height, and 17 cm in diameter, which is the basis of its holding capacity of approximately three kilograms of coffee cherries. The frame of the prototype is made up of 1×1 tubular steel, and round and flat bars. PVC pipes and 45-degree elbows were used to make the pipes that are directed to the bins. Hollow containers can be used as bins, but in case larger bins are needed, the prototype can be placed on top of an elevated surface such as a table, enabling larger bins to be properly positioned below it.

(a) (b)

Fig. 9. (a) Left and (b) front view of the device

For the GUI of the mobile app, the algorithm starts with the display of the login input and requires the user to enter their user credentials, which are their registered email and password. Upon a successful login, a confirmation message will be displayed, indicating that the account is valid, and the main user interface of the coffee cherry sorter will be displayed subsequently. After logging in, the home screen will appear as shown in Figure 10a, wherein there are two working buttons, namely the “Start Sorting” button to start the process and the “Reset” button to halt the process. At the lower half of the home screen, three boxes having labels of “Red”, “Green”, and “Black” are shown, which are the counters of the number of cherries sorted per their represented degree of ripeness. Figure 10b shows the menu, which is the three dots at the upper left of the screen, that has the “Reset Password”, “Logs”, and “Logout” options. The number of coffee cherries sorted each day is recorded and accessed through the “Logs” button from the menu, as shown in Figure 10c. Meanwhile, Figure 10d shows the screen that the application displays when live detection is ongoing, wherein the percentage is shown while the cherry is being scanned, distinguished by a green rectangle along with the ripeness label.

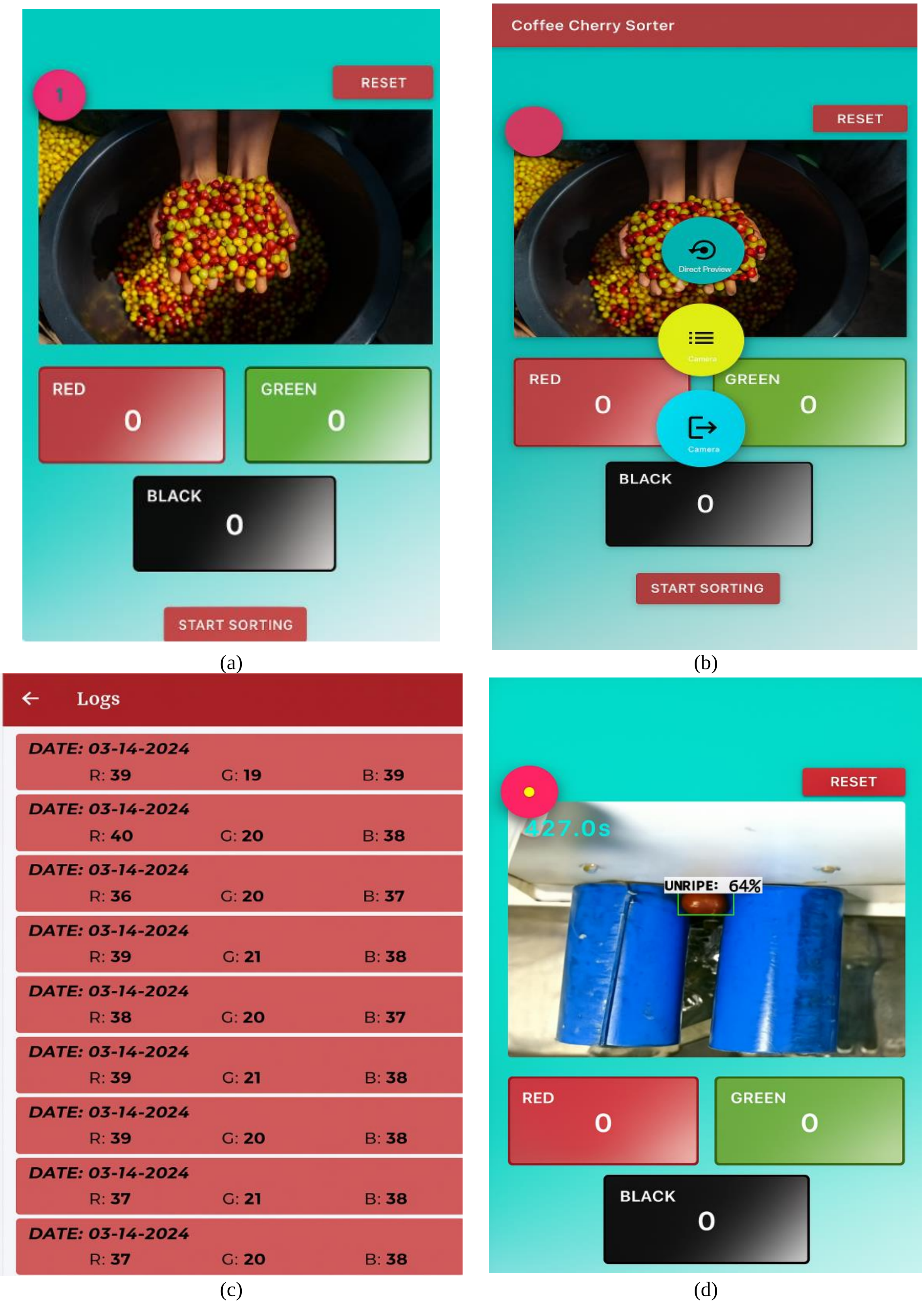


Fig. 10. App GUI: (a) home screen, (b) menu, (c) logs, and (d) ongoing sorting

CNN Model and Architecture

The architecture of the CNN was based on MobileNetV2 as the base network and the Single-shot multibox Detector (SSD) as the detection network, in which the entire model is part of the TensorFlow Object Detection API. The backbone of the SSD used in this study, which is MobileNetV2, has an initial fully convolutional layer with 32 filters followed by 19 residual bottleneck layers. Figure 11 shows the architecture of the CNN model, which consists of two types of blocks: the residual block of one stride and another block with two strides for downsizing. Both of these blocks have three layers, wherein the first layer includes a 1×1 convolution with ReLU6, the second layer includes depthwise convolution, and the third layer includes another 1×1 convolution with linearity. Reusing the rectified linear unit (ReLU) function has shown that deep networks can match the performance of a linear classifier across a non-zero volume portion of the output domain.

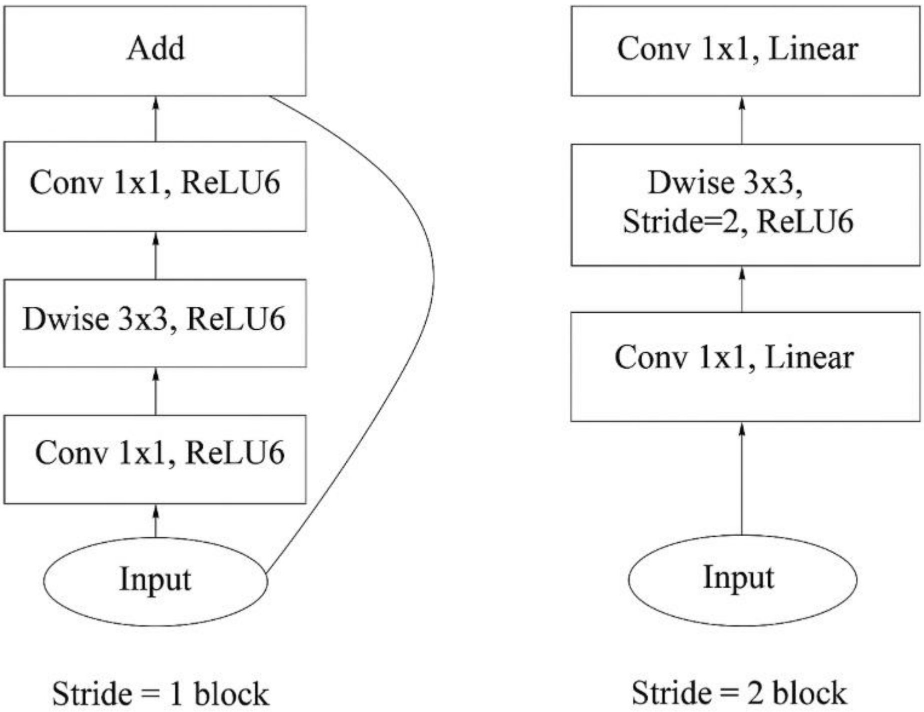
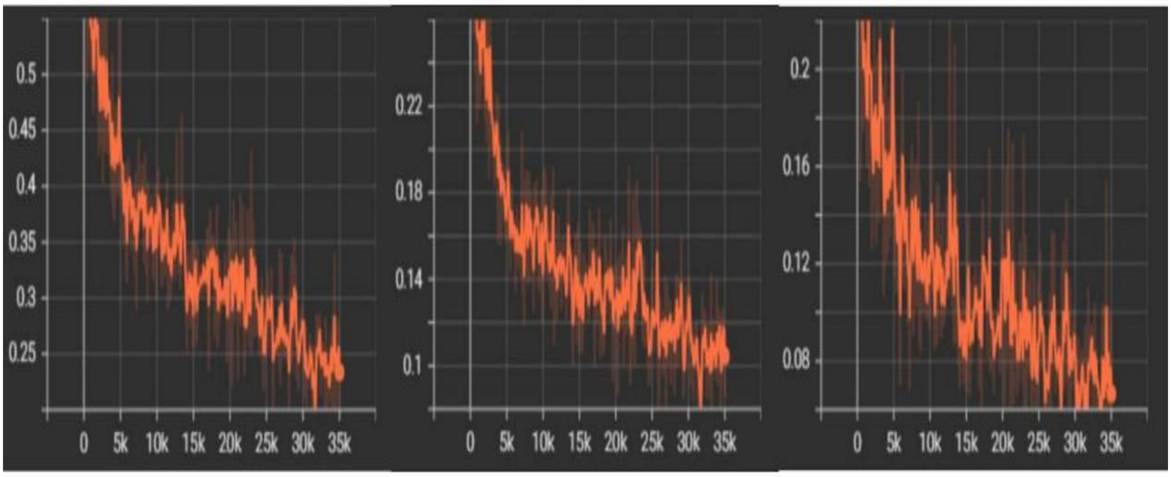


Fig. 11. Architecture of MobileNetV2

From a dataset of 5000 images, 4000 were allocated for training, with 500 images each designated for validation and testing, following an 80-10-10 percent division. Some data augmentation techniques, such as rotation and mirroring, were also performed to maximize the efficiency of the limited dataset, and the entire duration of training and validation took approximately 12 hours. Figure 12 shows the trained model's various loss functions, wherein the total loss is the overall loss of the model, and it decreased to 0.24 at the end of the epochs. At the classification stage, the loss decreased to 0.125, and the localization loss, which determines the position of the images, decreased to 0.01. From the total loss, the minimum model loss was almost zero, and the decrease of the model's losses was eventually observed to remain constant, which could be translated into the model's high accuracy rate in real-time detection.



(a) (b) (c)

Fig. 12. Model losses: (a) total loss, (b) classification loss, and (c) localization loss

Lastly, the model's testing dataset was used to determine its accuracy, where the program loaded the images, ran the detection model on each image, and displayed the results. Some of the displayed results from training are shown in Figure 13.

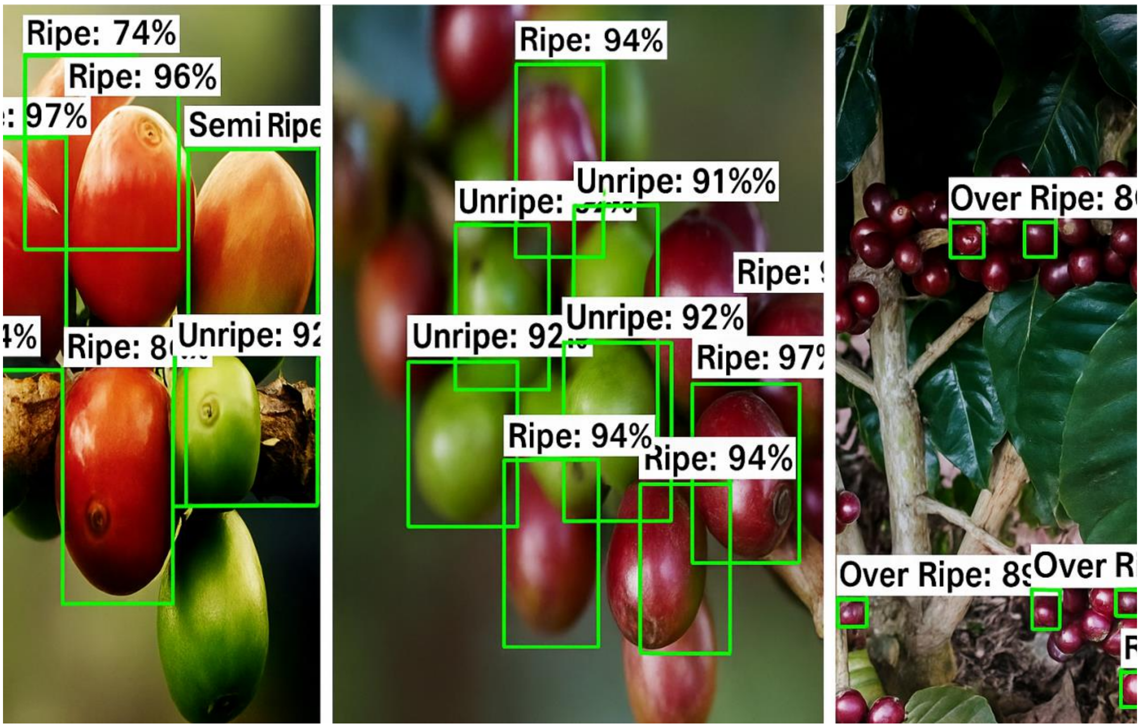


Fig. 13. Model testing result

Detection Model Accuracy and Precision

A total of 300 coffee cherries were used to obtain the detection model accuracy and precision wherein the samples were manually dropped into the scanning chamber to correctly tally the results. There are 60 unripe coffee cherry samples, 120 ripe, and 120 overripe for the actual classification as the ground truth of the model, which was based on the verification from National Coffee Research, Development, and Extension Center (NCRDEC) by making a gradient of the colors of coffee cherries on a maturation board. The model decides the classification by comparing the obtained percentage of ripeness after two detections of the same image, in which the higher percentage is the decided classification. Out of all the samples, 59 out of 60 unripe samples, 108 out of 120 ripe samples, and 110 out of 120 overripe samples were correct.

The comparison of the model's classification to the actual classification was summarized in a multi-class confusion matrix since there are three classes in order to obtain the model's overall accuracy and the precision of each class. Table 1 shows the summary of results of the model's classification in a confusion matrix wherein the diagonal cells are the correctly classified samples and are the true positive (TP) values. The samples that were incorrectly detected into the respective ripeness level are the false positive (FP) values and are the sum of the column values excluding the TP values. Those that were incorrectly detected as not belonging to that ripeness level were the false negative (FN) values and are the sum of the row values excluding the TP values. The samples correctly detected as not belonging to the respective ripeness level were the true negative (TN) values, which were obtained by subtracting the sum of TP, FP, and FN values from the total samples.

Table 1- Confusion matrix of model's classification

Actual Classification	Model's Classification		
	Unripe	Ripe	Overripe
Unripe	59	1	0
Ripe	1	108	11
Overripe	3	7	110

The model correctly detected 277 out of 300 samples, which resulted in an overall accuracy of 92.33 percent and indicates correctness across all classes in the confusion matrix. To tell the reliability of the model in detecting each ripeness level, each precision value in Table 1 was calculated. The TP, FP, FN, and TN values were needed to calculate these. The unripe category had the highest precision of 93.65 percent, while the ripe and overripe categories had precisions of 93.1 percent and 90.91 percent, respectively.

Sorting Speed and Accuracy

In order to obtain the right speed setting for the stepper motor of the hopper, the researchers conducted 10 trials each using 20 samples of all the colors of coffee cherries. There were four speed settings selected to conduct those trials, which were based on the revolutions per minute (rpm) that the stepper motor could appropriately execute; the speed settings selected are 100 rpm, 200 rpm, 300 rpm, and 400 rpm, which were observed to be the intervals with significant difference. Table 2 presents the summary of the results of speed trial. The accuracy was obtained from dividing the correctly sorted coffee cherries by the total samples.

Table 2- Speed testing of stepper motor for the hopper

Speed (rpm)	Time taken (minutes)	Accuracy (%)	Did clogging occur?
100	5:48	92.0	No
200	3:54	91.5	No
300	2:11	91.0	No
400	1:36	85.5	Yes

The speed setting of 300 rpm was chosen for the device since it had the fastest time with reliable accuracy. The accuracy achieved at 100 rpm and 200 rpm was marginally higher; however, due to the considerably longer sorting times at these speeds compared to the

300 rpm, they were not selected. At 400 rpm, while it may achieve the quickest processing time, the accuracy is considerably compromised due to some samples becoming clogged. A speed setting of 500 rpm was tested; however, it wasn't documented due to inadequate sorting, leading to the conclusion that it was unsuitable for the device.

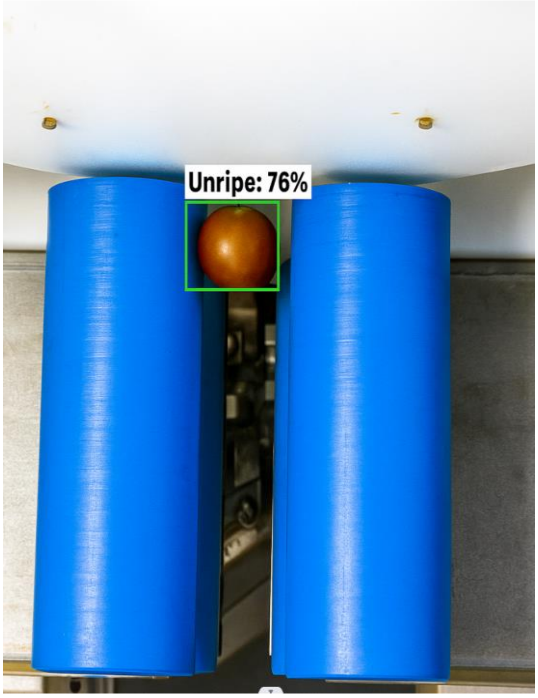
After selecting the right speed setting, trials were conducted to obtain the device's sorting speed and accuracy. There were a total of 1000 samples of coffee cherries used, with 200 unripe, 400 ripe, and 400 overripe. Then, they were divided into 10 trials, so each trial used 100 samples each, with 20 unripe, 40 ripe, and 40 overripe. The summary of the results from the 10 trials conducted is shown in Table 3. Out of 1000 samples, 890 cherries were correctly sorted to the right bins across all trials.

The overall machine accuracy achieved throughout all trials stands at 86.83 percent, with an error rate of 4.7 percent, calculated based on missed samples relative to the total samples. Table 3 has an assigned column for the cherries that were not sorted during the process because of the machine design constraints; there were instances where the cherry went straight to the bin without being scanned, hence this number was included in the equation used. For the speed of the sorting process, on the other hand, the average time obtained for 100 samples was 21 minutes and 33 seconds, equivalent to 12.9 seconds per cherry, in which the timer started as soon as the cherries were fed into the hop

Table 3- Summary of machine trials

Trial	Correctly Sorted	Incorrectly Sorted	Not Sorted	Total	Minutes (Average)	Accuracy (Average)
1	89	8	3	100	20.90	86.33
2	92	6	2	100	22.27	90.67
3	89	6	5	100	23.18	87.17
4	88	8	4	100	21.12	86.00
5	89	6	5	100	22.97	87.17
6	91	5	4	100	22.05	88.67
7	86	4	10	100	19.47	82.83
8	87	8	5	100	20.03	84.83
9	89	5	6	100	22.05	86.33
10	90	7	3	100	21.52	88.33
Total	890	63	47	1000	21.56	86.83

Prior to this, the initial time taken by the device to sort the samples was 29.4 seconds per cherry, as it took 49 minutes to sort 100 coffee cherries. Since this was deemed to be too slow for the device's speed, the researchers adjusted the resolution of the image to 256×256 pixels from the original 1280×720 pixels. The frame captured by the camera was also zoomed, so it did not process more details from the background, as shown in Figure 14. Some program adjustments were also done, such as reducing the delays of the motors. As a result, the speed of final testing improved by over 50% compared to initial testing while maintaining accuracy.



(a) (b)

Fig. 14. Camera frame: (a) initial test (b) final test

The device was evaluated to determine whether it could sustain a three-kilogram load in the hopper, according to its measured dimensions. Because the samples were only weighed and fed into the hopper randomly without being counted, there was no reliable method to establish their accuracy. Therefore, the researchers only counted the number of cherries that were not sorted and the time it took to sort the samples. The mobile app displayed a total count of 3103 coffee cherries sorted, as shown in Figure 15, and after counting, 152 cherries were not sorted, which equates to an error rate of 4.9 percent. It took 11.5 hours to sort, including the time that the camera had to be unplugged for one hour before re-plugging, as it cannot hold out for those continuous hours.

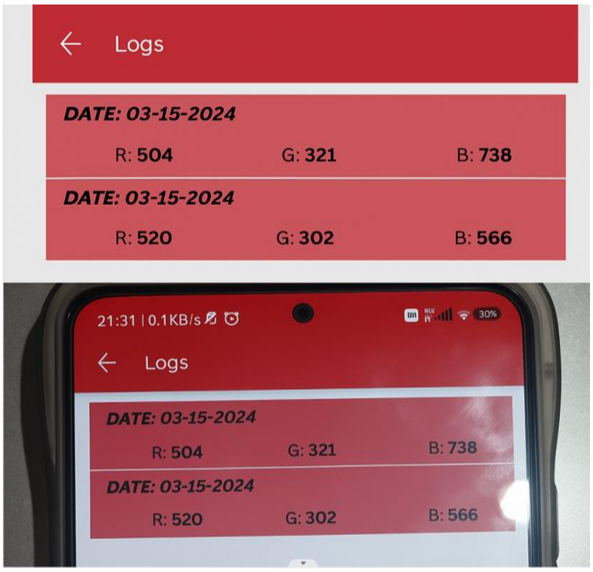


Fig. 15. Logged count of 3 kg of coffee cherries

The internet speed should be taken into account for the average machine speed obtained, since there were instances where the motors did not move as timely as they were programmed because of constraints in the internet connection. The average seconds taken for each of the components—the hopper, the rollers, the moving pipe, and the moving hand—to move was recorded for each of the first 100 properly sorted cherries, which were divided into 10 trials with 10 cherries each. Table 4 shows the summary of the results. The speed of the hopper was recorded as soon as it began spinning, right until the cherry dropped into the tube pipe. For the speed of the rollers, it was timed on how fast it rolls the cherry, while for the moving pipe, it was timed on how fast it moved and stopped at the right pipe directed to the bin. The moving hand was timed on how fast it flicked the cherry.

Table 4- Summary of speed trials of each component

Trial	Time (s)			
	Hopper	**Rollers**	**Moving pipe**	**Moving hand**
1	4.11	2.08	2.18	1.60
2	3.89	2.07	2.20	1.44
3	4.29	2.03	2.25	1.56
4	3.92	2.15	2.27	1.58
5	4.03	2.03	2.23	1.40
6	3.99	1.99	2.28	1.50
7	3.95	2.01	2.24	1.47
8	4.01	2.04	2.25	1.77
9	3.81	2.07	2.23	1.24
10	4.09	2.03	2.24	1.62
Average	4.01	2.05	2.24	1.52

IoT Mobile Application Features

The IoT mobile application was tested on how fast the device starts and stops when the app is used, on how correctly it logs the number of sorted coffee cherries, on how synched the real-time detection video is, and on how reliable the notification is.

The recorded speed of how fast the device started after app activation was an average of 3.94 seconds and an average of 6.07 seconds on how fast it stopped after deactivation. The app also correctly counted all of the samples, as the number matched the data tallied after counting the content of the bins when the sorting stopped. For how synchronized the real-time detection video is, the researchers tallied the seconds it took for the first cherry of each trial to appear on the app after dropping into the scanning chamber, since the next cherries to drop would appear in that interval, which took an average of 7.05 seconds across all trials. Lastly, the reliability of the device's notification was also tested. Figure 16 shows that the device notified the user in a five-minute interval when the camera did not detect anything. When the camera is detecting something, the device does not send any notifications.

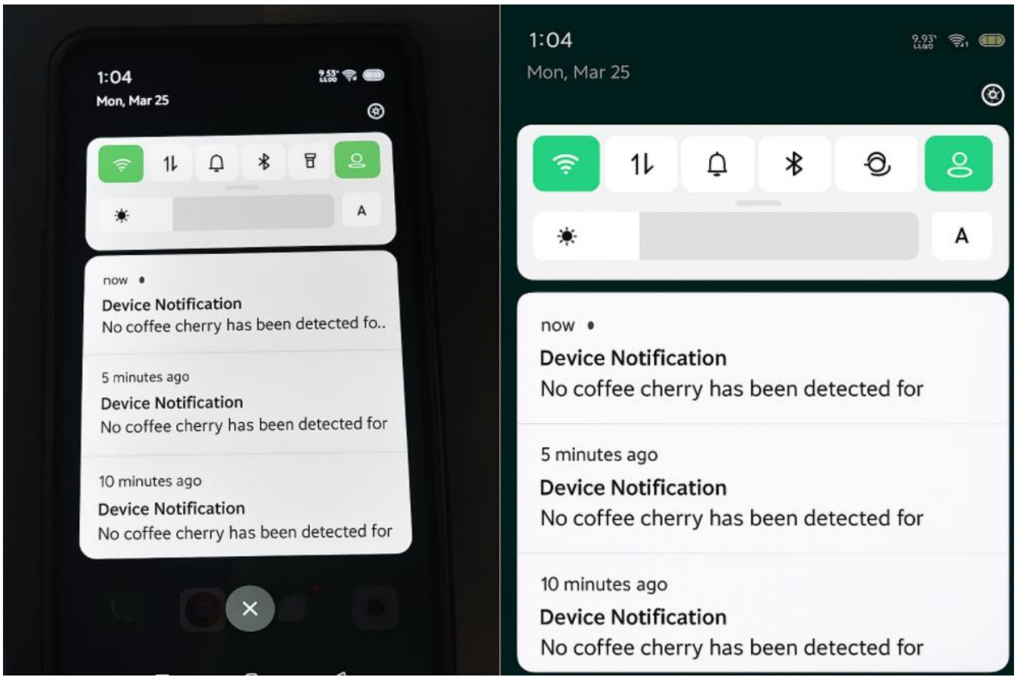


Fig. 16. 5-minute interval of device notification

The researchers conducted a comparative assessment between their developed prototype and another project developed by Bondal, Lunes, and Llanto (2011) titled "Design and Development of Microcontroller-based Coffee Color Sorter" in terms of the obtained machine speed and accuracy. The referenced study also sorted the coffee cherries by color, specifically green, red, and black, and analyzed them according to the same metrics of speed and accuracy. However, it used a color sensor and a different microcontroller for the device's program. It had also implemented a conveyor system, which is different from the developed machine design of this study. Figure 17 shows the accuracy comparison of the two devices, wherein the developed prototype of this study is observed to have a significantly higher accuracy of 86.83 percent than the existing study's 60.84 percent.

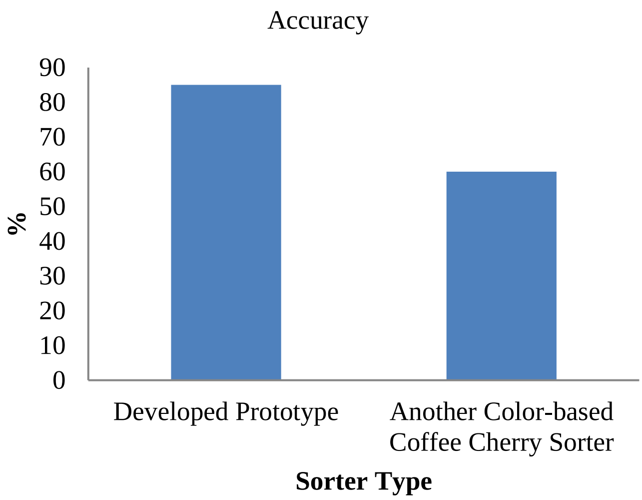


Fig. 17. Accuracy comparison of the study and the other color-based coffee cherry sorting machine

On the other hand, Figure 18 shows the speed comparison of the two devices. The existing study took an average of 56 minutes to sort 100 cherries, resulting in 33.6 seconds per cherry over three trials. In comparison, this study finished the sorting process in just 21.5 minutes, averaging 12.9 seconds per cherry over ten trials, signifying a substantial decrease in time required.

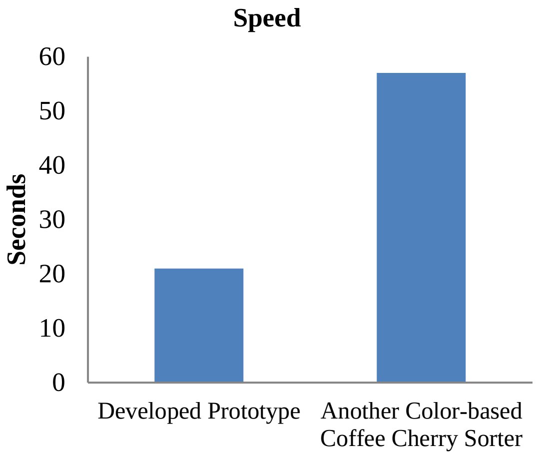


Fig. 18. Speed comparison of the study and the other color-based coffee cherry sorting machine

Several studies have proposed automated sorting of various agricultural products based on image processing, which obtained significant results. Abbas, Shakoor, Khan, Ahmed, and Khurshid (2019) conducted a study with the purpose of creating machine-controlled fruit sorting using image processing in order to achieve higher quality fruit sorting, quality maintenance and production, and to reduce labor. It concluded that automatic fruit sorting using image processing is a strong and economical system compared to existing manual sorting systems. Another study by Injante, Gutierrez, and Vinces (2020) proposed developing an automatic sorting machine using image processing algorithms for sorting lima beans, wherein an efficiency of 96.81 percent in acceptance of good beans and 95.26 percent in rejection of defective beans was achieved. This study contributed another perspective in this field by using CNN as a detection algorithm for sorting samples based on their colors.

The prototype developed was not directly compared to existing commercial coffee sorting machines for several important reasons. Firstly, commercial coffee sorting systems are generally built for large-scale industrial use and often involve expensive, proprietary hardware and software that are not readily available for comparison or technical assessment. In contrast, the prototype discussed in this study is designed as a low-cost, scalable option specifically for smallholder farmers and local cooperatives in developing areas, where access to such commercial systems is either limited or not financially viable.

Secondly, this research aimed to enhance previously created academic prototypes within similar operational and resource-limited environments, providing a more relevant basis for assessing practical improvements in performance, cost-effectiveness, and accessibility. The integration of IoT capabilities and the use of a Raspberry Pi platform also distinguish this device in terms of its intended use and system design.

Future research may involve comparative analyses with commercial systems where possible, especially regarding throughput, accuracy, and operational costs, to further confirm the prototype's advantages and limitations in real-world agricultural contexts.

Conclusion

The researchers concluded that the objectives of the development of an IoT automated color-based sorting machine for Robusta coffee cherries were all successfully met from the data gathered and evaluated. The machine construction, which was designed to have less human interference, was accomplished along with the circuitry. The machine design consists of a hopper, a sorting chamber with the rollers and the moving hand, and the pipes directed to the bins. Because of the spinning disk inside the hopper, the cherries dropped one at a time and clogging was avoided. The rollers were also able to spin the cherry and have the camera scan its entirety.

The detection algorithm based on image processing was done with a CNN-based detection model, which after training, showed stabilized losses, reflecting remarkable accuracy for real-time detections. It was evaluated through a confusion matrix that tallied the actual classification and the prototype's classification of the samples, which yielded reliable accuracy and precision. The unripe category had the highest precision, while the ripe and overripe categories came just close.

The researchers were also able to implement an IoT-based ripeness classifier system and develop a mobile application that stores data and notifies the user. The app was able to count all the cherries sorted per ripeness category and store them on the app. Additionally, the notification was evaluated to be reliable, as it was provided whenever a coffee cherry had not been detected for five minutes, while it does not notify when the detection is ongoing.

The tested sorting accuracy and speed of the device were all translated to having a reliable and good performance from the 10 trials conducted using a total of 1000 coffee cherry samples. Necessary adjustments were made to the program so the speed of final testing reduced by half compared to initial testing. This device surpasses existing coffee cherry sorting machines by offering greater precision and faster processing speeds.

Authors Contribution

M. K. Alano: The author constructed the circuit for the IoT Automated Color-based Sorting Machine for Robusta Coffee Cherries (Coffea canephora). She also tested and evaluated the developed system.

V. Ogaya: The author constructed the circuit for the IoT Automated Color-based Sorting Machine for Robusta Coffee Cherries (Coffea canephora). She also tested and evaluated the developed system.

E. Arboleda: The author contributed the following: conceptualization of the research idea, supervision in the conduct of the study, provided technical advice as well as devised the methodology for this study. The author also performed the writing, review and editing of the manuscript in a publishable format.

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توسعه سامانه هوشمند اینترنت اشیا برای درجه‌بندی خودکار دانه‌های قهوه روبوستا (*Coffea canephora*) بر پایه رنگ

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چکیده

تمرکز این تحقیق ایجاد یک دستگاه مبتنی بر اینترنت اشیا برای درجه‌بندی دانه‌های قهوه روبوستا بر اساس رنگ است که از پردازش تصویر به‌عنوان جایگزینی موثر برای جداسازی دستی استفاده می‌کند. این سیستم به رفع یک مشکل مهم در روش برداشت نواری می‌پردازد که دانه‌ها را در درجات مختلف رسیدگی جمع‌آوری می‌کند و تاثیر منفی بر کیفیت قهوه می‌گذارد. این دستگاه، دانه‌ها را بر اساس درجه رسیدگی –قرمز برای رسیده، سبز برای نارس و سیاه برای بیش از حد رسیده– با استفاده از یک مدل تشخیص که از طریق پردازش تصویر آموزش دیده و بر روی Raspberry Pi 4 Model B پیاده‌سازی شده است، مرتب می‌کند. عملکرد دستگاه بر اساس سرعت مرتب‌سازی و دقت طبقه‌بندی ارزیابی شد. مدل تشخیص با موفقیت ۲۷۷ از ۳۰۰ میوه قهوه را شناسایی کرد که منجر به دقت طبقه‌بندی کلی ۹۲/۳۳٪ و میانگین دقت ۹۲/۵۵ ٪ شد. در آزمایش‌های عملی با ۱۰۰ نمونه دانه در ۱۰ آزمایش، دستگاه به‌طور متوسط به دقت دسته‌بندی ۸۶/۸۳٪ و زمان دسته‌بندی ۲۱ دقیقه و ۳۳ ثانیه دست یافت. در مقایسه با دستگاه دسته‌بندی دانه‌های قهوه که قبلا توسعه داده شده است، در دستگاه جدید دقت بهبودیافته و سرعت پردازش سریع‌تری را نشان داد.

واژه‌های کلیدی: برداشت نواری، پردازش تصویر، سورتینگ، شبکه عصبی کانولوشن

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