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Development and Testing of Green Coffee Bean Quality Sorter using Image Processing and Artificial Neural Network

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Abstract

Currently, the Philippines has no commercially available coffee bean sorter to mechanize the manual sorting, which is prone to human errors. Hence, this study aimed to design and develop a green coffee bean (GCB) quality sorter using various electronic materials for the sorting mechanism, a proportional-integral-derivative (PID)-based algorithm and image processing as sorting system control, and other locally available materials for the machine's framework. The developed prototype was then evaluated through preliminary testing. A series of tests in three trials were conducted with different sets of Arabica GCBs (T1: 120 good GCBs, T2: 120 defective GCBs, T3: 100 good GCBs + 20 defective GCBs, T4: 20 good GCBs + 100 defective GCBs, and T5: 60 good GCBs + 60 defective GCBs) as test materials. It was shown that the machine can separate defective from the good GCBs arranged in linearity using neural network and image processing. Two webcams were installed to take images of both sides of the bean, which were used for determining the GCB quality through a prediction test. The device was found to be functional with an accuracy of 89.17%, which was comparable with manual sorting. Furthermore, the machine can sort 1 kg of GCBs within 2 h and 45 min. The preliminary tests' results can be used as reference in designing similar equipment.

Keywords: accuracy test, green coffee bean sorter, PID algorithm and controller, postharvest equipment

1. Introduction

Coffee is considered an export-oriented agricultural commodity earning around 20 billion US dollars a year (International Coffee Association [ICO], 2019). In 2018, world coffee production was accounted to be at 174,897,000 bags (60 kg per bag) of green coffee beans (GCBs) while the total global consumption in 2018 and 2019 was recorded at 167,936,000 bags (60 kg per bag) of GCBs (ICO, 2020). With these figures, it is no wonder that coffee is known as one of the most famous beverages consumed worldwide (Ferrão *et al*., 2015; Semen *et al*., 2017; Sunarharum *et al*., 2018; Yusmanizar *et al*., 2019); the daily and annual estimated coffee consumptions are more than two billion (Garcia *et al*., 2019) and about 600 billion of cups, respectively (Pereira *et al*., 2017). The popularity of coffee products is driven by their unique sensory attributes (i.e., taste and aroma), pleasant flavor profile and some nutritive value (Pereira *et al*., 2019; Yusmanizar *et al*., 2019).

Coffee is normally served in a cup after the coffee beans are roasted, ground and brewed. There are different types of coffee roasts and grind; however, all coffee beverages start from GCBs. GCBs refer to unroasted or raw seeds from the coffee fruits (Semen *et al*., 2017; Pereira *et al*., 2019). GCB is still the major form of valuable coffee product in the international trade (Franca *et al*., 2005) wherein quality is of great importance. The demand and consumption of high-quality coffee are constantly increasing every year (Sunarharum *et al*., 2018; Giacalone *et al*., 2019). Therefore, the quality of coffee beans dictates their price value (Faridah *et al*., 2011), storage stability and general consumer acceptability (Garcia *et al*., 2019). The quality of GCBs is measured according to their size, shape, color, processing method used, crop year, roasting characteristics, cup quality and presence of defects (Banks *et al*., 1999; Ramalakshmi *et al*., 2007; Garcia *et al*., 2019). Among all the mentioned quality attributes, cup quality or flavor profile and the presence of defective beans are the most significant since the international coffee trading uses the said criteria (Franca *et al*., 2005; Mancha Agresti *et al*., 2008). An annual estimate of 1.2 to 1.5 million defective beans is generated by the coffee industry and rejected by the international market – that is about 15 to 20% of the total global coffee production (Ramalakshmi *et al*., 2007).

The presence of defective beans directly affects the cup quality of the coffee beverage. Defective beans are black, sour, brown, immature, insect-damaged, or bored and have foreign materials like twigs, husks and sticks, which are considered in coffee quality assurance and used for determining the samples' grade (Franca *et al*., 2005; Mancha Agresti *et al*., 2008; Datov and Lin, 2019). These defects are obtained as a result of the indecorous formation of beans within the fruit, problems during the harvesting and pre-processing operations and improper post-harvest or processing methods (Franca *et al*., 2005; Ramalakshmi *et al*., 2007).

In other countries, several studies were done to automate or mechanize the manual system of identifying GCB defects. The study of de Oliveira *et al.* (2015) used a computer vision system for classifying the defects based on color resulting in 100% accuracy. Other works employed hyperspectral image analysis (Backhaus *et al.*, 2012; Calvini *et al.*, 2015) and artificial vision or machine learning (Carrillo and Peñaloza, 2009; Faridah *et al.*, 2011; Pinto *et al.*, 2017; Garcia *et al.*, 2019). However, in the Philippines, there is still no commercially available GCB quality sorting machine. Coffee processors opt to do manual sorting which is time-consuming, labor-intensive, subjective and prone to human errors.

In an attempt to automate the system for defect classification of GCBs, this study aimed to develop a mechanical GCB quality sorter with the aid of image processing and artificial neural network and evaluate this machine through preliminary testing.

2. Methodology

2.1 Materials for Machine Development

Table 1 shows the materials used for the sorting mechanism of the developed GCB quality sorter. The assembly of the sorting mechanism was composed of electronic parts, cameras, lights and software for image processing. Other materials were also used for the fabrication of the machine such as connecting wires, universal serial bus (USB) hubs, acrylic glass and aluminum sheets for the machine's framework.

2.2 Machine Design and Development

The developed GCB quality sorter has a height of 60.96 cm and a width of 50.8 cm as shown in Figure 1. The dimension of the hopper or the funnel type input chute (1), where the GCBs are manually placed, were 10.16 cm (height), 6.35 cm (width) and 15.24 cm (length). The sorter has a servo motor that can open and close to provide more efficient control and prevent GCBs to be displaced from each other. The servo motor also limited the number of GCBs that were accepted by the machine per operating period. Moreover, aluminum frameworks with guides were placed at the top of a circular acrylic glass conveyor (2) to navigate and move the GCBs to the camera sensor to capture and process the image, and sort the GCBs. A circular glass conveyor was used since it is a transparent material allowing the camera to take images of the sides of the GCB rather than using the traditional conveyor belts, which are opaque. The conveyor arranged the GCBs in a linear manner that made sorting more organized. The glass was controlled by the stepper motor. A door-like piece of aluminum, acting as a flipper, was installed to separate the good and defective GCBs. Since the glass material and the aluminum framework are directly in contact with the GCBs, these materials must be safe from other contaminants to avoid possible defects that may infest the beans.

Table 1. Materials used for the development of the machine (sorting mechanism)

Materials	Quantity	Feature	Function	Model, manufacturer*, and country of origin
Arduino Uno	1 unit	It is a microcontroller environmental board based on the Microchip Atmega328P. It is equipped with 13 digital and six analog input/output pins that can interface with numerous expansion boards and other circuits.	It served as the main controller of the machine.	Makerlab Electronics, Philippines
1080P full-HD web camera	2 units	A webcam type camera which has an image array capable of operating at up to 30 frames per second (fps) in VGA with complete user control over image quality, formatting, and output data transfer.	They were used to capture images of the GCBs inputted/entered into the machine.	PK-920H, A4TECH, Taiwan
Mini gear micro servo motor	1 unit	It is a rotary actuator or linear actuator that allows for precise control of angular or linear position, velocity, and accelerat ion.	It was utilized to control the door-like piece of aluminum that separated the good and defective GCBs.	SG90, China

Table 1 continued.

NEMA 23 stepper motor	1 unit	It is a digital version of the electric motors that enable accurate positioning.	It was used for the circular movement of the conveyor.	57HS56-3004, Philippines
Stepper motor driver	1 unit	It transmits signals and functions as an interface between the microcontroller and motor.	It controlled the NEMA 23 stepper motor.	DQ542MA, Makerlab Electronics, Philippines
Rotary encoder	1 unit	It is a sensor that detects position and speed by converting rotational mechanical displacements into electrical signals and processing the said signals.	It was used to adjust the stepper motor mounted on the rotating plate to a proper position.	SparkFun Electronics, United States
Switching power supply	1 unit	It is an electrical device that converts 220 V alternating current (AC) power into 24V, 12V, and 5V direct current (DC) power.	It served as main power source of the machine.	Philippines
Light emitting diode (LED) strip	4 m	It consists of many individual LED emitters mounted on a narrow, flexible circuit board.	It was used to allow the effectiveness of the image processing system and ensure the good quality of the captured images.	OMNI Electrical and Lighting, Philippines
MATrix LABoratory (MATLAB) version 2019 software	1 unit	It allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces and interfacing with programs written in other languages.	It was used for the image processing function of the system and the Arduino integrated development environment (IDE) for the programming of the microcontroller.	MathWorks Inc., United States

*Some materials used had either no model or manufacturer (or both) on their packaging upon purchase.

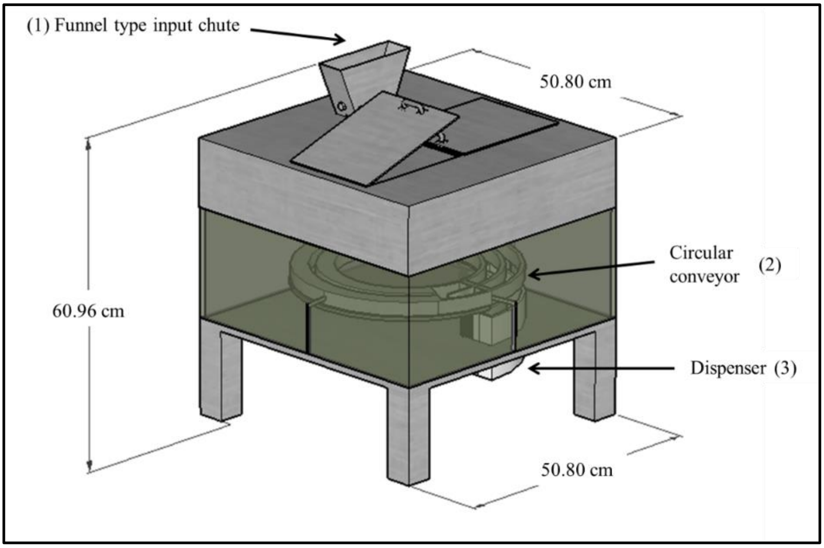

Figure 1. Design of the GCB quality sorter

The two web cameras were selected based on their speed in capturing images in continuous shot mode. The cameras were installed parallel to each other to capture the top and bottom parts of the GCB. The captured images were then transferred to the computer. LED strips were placed along the aluminum guides to provide lighting to enhance the quality of the captured images of the camera for more accurate findings. The dispenser (3) was directed to a container to collect the good and bad GCBs. An alternating current (AC) to direct current (DC) converter was used to supply power to the sorter. The 220-V AC source was transformed into 24, 12, or 5 V DC to supply power to the different motors and other components of the system.

2.3 Application of Image Processing, Cameras, Proportional-Integral-Derivative (PID) Algorithm and Neural Network

As mentioned above, two cameras and LED strips as lighting sources were systematically placed inside the sorting machine to capture high-definition images of each side of the GCBs, thereby implementing the image processing algorithm and network. The network can only identify GCBs if the image stored in the network is a picture of a singular bean. The GCBs must be arranged linearly to reduce the confusion in the network. The movement of the GCBs must only be in a singular direction and they should not fall off the platform to properly implement the sorting.

The images used MATLAB® version 2019 for image processing. The cameras continuously took images of the GCBs; the captured images were then pre-processed, entered into the neural network, and then processed in the MATLAB®. The software was used to design and develop a neural network with a training dataset of GCB quality standards. The standards for the image processing network were based on the Specialty Coffee Association of America ([SCAA], 2018) green coffee grading protocol and the Bureau of Agriculture and Fisheries Standards ([BAFS], 2012) for GCBs. The machine was trained to capture images of GCBs that were aligned by the aluminum guides. The camera then sent signals to the computer that analyzed and processed the image. A decision was made by the software whether to accept or reject the GCBs. The image of the individual GCB was processed and its quality was determined. Depending on the finding, the software sent a serial signal to the microcontroller. The microcontroller was utilized to manipulate the servo motor that controlled the flipper that separated the good and the defective ones. After separating, the GCBs were dropped according to their corresponding output chute. The PID algorithm was used to increase the accuracy of the sorter and the learning speed of the sorting system. The block diagram of the PID controller-based GCB quality sorter is shown in Figure 2.

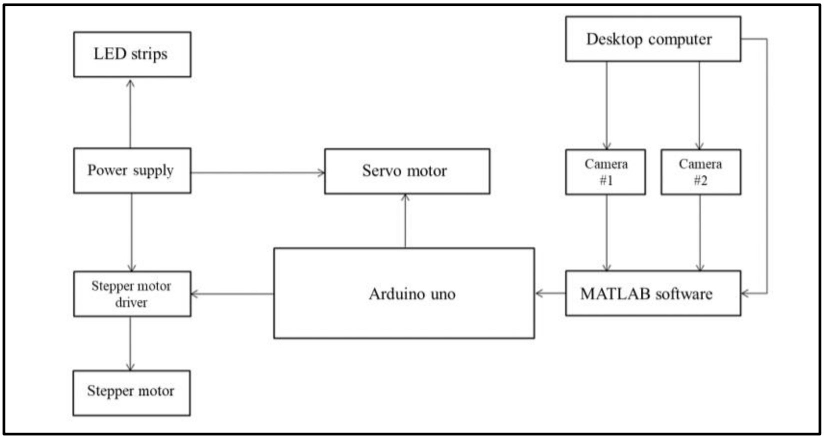

Figure 2. Block diagram of the GCB quality sorter with PID algorithm as sorting system control

On the other hand, the neural network used to implement the image processing algorithm was trained in the MATLAB®. The GCB was first detected by the object detection network. The object detector – the YOLOv2 network provided by MathWorks – has 24 hidden layers and two fully connected layers. The network was then coded using the GPU Coder™ to increase its speed. The network took snapshots of the bottom webcam; the returned image was then tested in the network. Bounding boxes were automatically placed on the GCBs taken by the webcam. A constant center box was then placed. After which, the network would test if a GCB is positioned inside of the center box. If no GCB is detected, the network will send a serial variable to the microcontroller, increasing a step to the stepper motor. If a GCB is detected, the bounding box is cropped, and the picture of the singular bean is transferred to the quality identifier network.

The quality identifier network was a neural network similar to the InceptionV3 network. It has 42 hidden layers making it one of the deepest neural networks available. The network has one input node and six output nodes corresponding to three possible outcomes of the network and two sides of the GCB. The GCB is determined to be good if the network finds both sides of it as good. The three possible outcomes per side are black bean (dark and infected), deformed bean (broken with holes and irregular shape) and good bean.

The defects were predetermined based on the Philippine National Standards (PNS) (BFAS, 2012) and SCAA (2018) for GCBs. There were six classification categories for the GCBs, which were labeled as follows: back good, back black, back deformed, front good, front black and front deformed. The researchers took and cropped 1,000 images of GCB per category (6,000 images in total) to train the neural network. The network was trained for 2 h with the MATLAB®. The sample images taken are shown in Figures 3 to 5.

2.4 Program Development for MATLAB® and Arduino IDE

To implement the sorting algorithm, MATLAB® was used. It has a command window and built-in functions that were used for image processing. The sorting machine sent data to MATLAB® individually and MATLAB® processed the image with the preset algorithm provided by the researchers. Once the cameras detected a GCB and identified its quality, the software sent signals to the servo motor and separated the GCBs depending on their quality. The software also determined when the controllers moved and how much input the sorter accepted. Figure 6 shows the system flowchart of the machine.

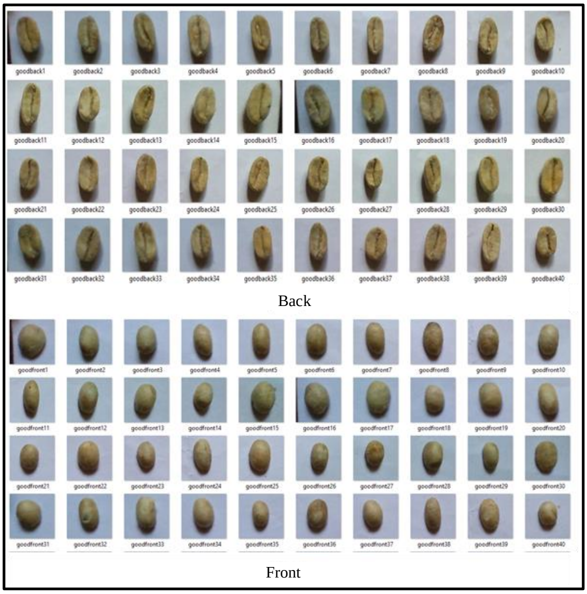

Figure 3. Sample data set for training the quality detector for good GCBs

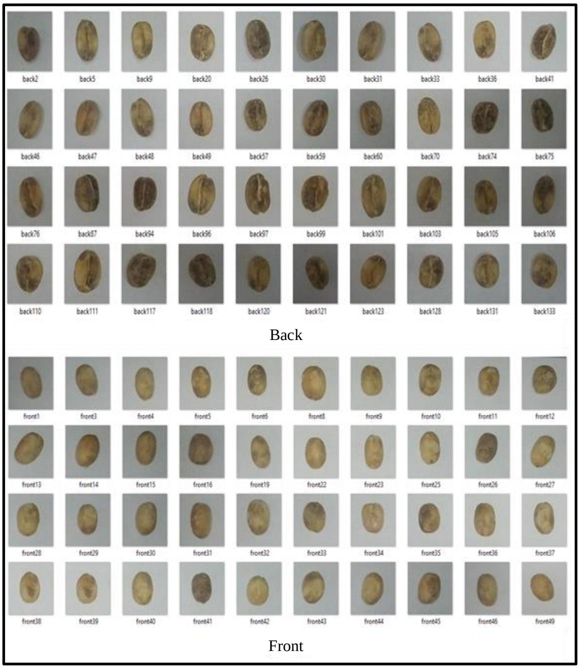

Figure 4. Sample data set for training the quality detector for defective (black) GCBs

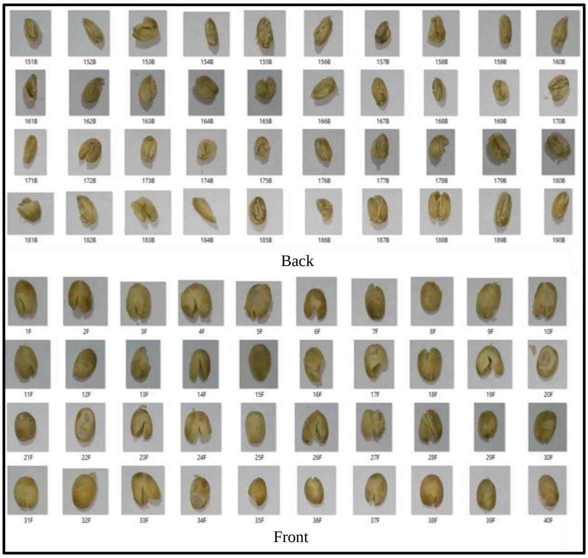

Figure 5. Sample data set for training the quality detector for defective (deformed) GCBs

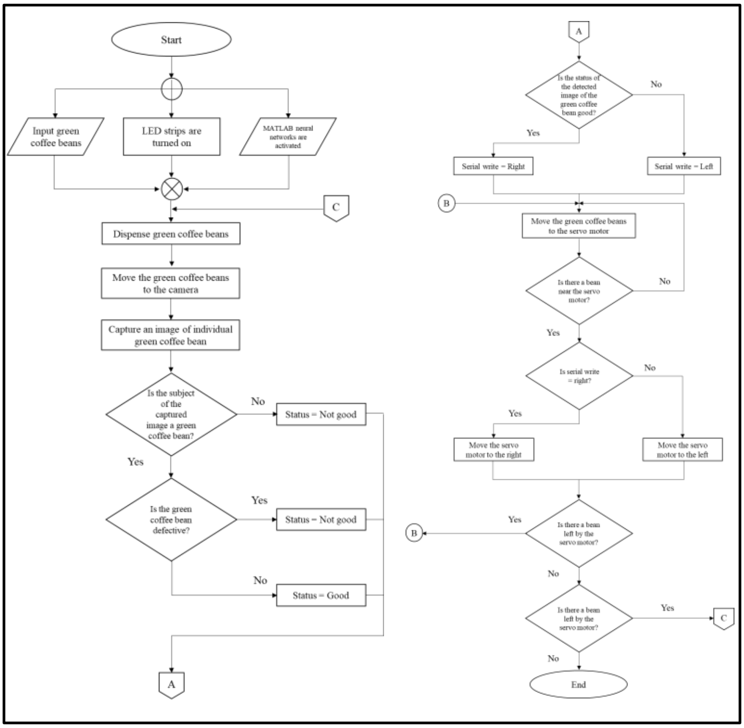

Figure 6. System flowchart of PID controller-based GCB quality sorter

2.5 Circuit Design

The circuit of the device consisted of the interconnection of all components used in the system. Two circuits were used, namely the main and light circuits. The main circuit was supplied by the 24-V switching power supply and 5-V USB input from the USB port of the computer. The 24 V were utilized to supply the stepper motor and the stepper motor driver while the 5 V from the USB port supplied the power needed by the servo motors and the rotary encoder. Figure 7 shows the whole circuit diagram of the system.

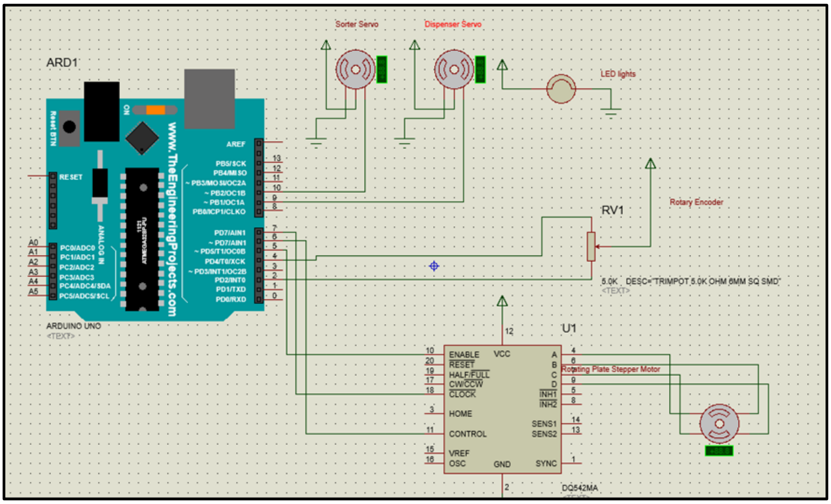

Figure 7. Circuit diagram of the PID controller-based GCB quality sorter

As shown in the circuit, the servo motor responsible for sorting the beans was assigned to digital pin D9. The stepper motor driver enabled pin was assigned to pin D5 of the Arduino microcontroller board. The direction pin was assigned to pin D6 and the step pin was connected to pin D7. All the motors shared a common ground. The lights of the machine had an individual circuit separate from the other motors. It was connected directly to the 12-V output of the switching power supply.

The stepper motor has four pins that are connected to the stepper motor driver. They provided control to the stepper motor signaling when would the stepper move by manipulating the current that passed through any of the two output wires triggering the magnets inside the stepper motor. The stepper motor driver was configured to give only 2 A to the stepper motor to prevent overheating and requires 1,600 steps to complete a revolution.

2.6 Principles of Machine Operation

The machine (Figure 8) is activated by plugging the power supply into an ordinary 220-V, 60-Hz AC socket and opening the M file script in the MATLAB®. A computer was set up to provide serial communication between the microcontroller and the designed neural network. The lights and stepper motor were connected to the power supply providing 24 and 12 V DC, respectively. The two webcams and the type B USB cord were plugged into the USB ports of the desktop computer. The Arduino program was uploaded to the board and the MATLAB® M file was run in the command window.

Figure 8. The developed GCB quality sorter

After setting up the machine, the machine's serial communication was established. The serial communication was implemented in the first lines of the M file in the MATLAB® software. Once the communication was established, all the Arduino components were initialized, and the cameras were activated. A rotary encoder was provided to adjust the stepper motor-mounted rotating plate to a proper position. Once set, the GCBs were poured into the machine through the hopper.

To ensure the speed of the neural network operations supported in MATLAB®, the MATLAB® software was installed on a computer with the following features: operating system – Windows 10, RAM – 8 GB, free space in the hard disk – 22 GB and memory graphics card – 2 GB. The system also had a prolific driver to allow serial communication between the machine and the computer. The Arduino IDE not older than 1.6.11 was also installed on the computer.

2.7 Preliminary Testing

To ensure the effectiveness and the reliability of the machine regarding its functionalities, the machine underwent three sets of tests to be considered a successful design: functionality, accuracy and speed tests using Arabica GCBs as test materials.

2.7.1 Functionality Test

The functionality test was employed to test whether or not the different motors and controllers moved according to the time and setting that they were given. Moreover, the object detection algorithm, quality identifier algorithm, motor control algorithm, and sorting mechanism developed were evaluated by initiating numerous tests with a controlled amount of GCBs. The GCBs' quality was already identified beforehand, and the system must identify the quality of the bean and sort them into their respective columns.

2.7.2 Accuracy Test

The accuracy test was carried out to determine the accuracy of the sorter. The GCB samples were obtained from the National Coffee Research, Development and Extension Center (NCRDEC). The GCB database was programmed into the MATLAB® and used for image processing. To test the accuracy of the machine, numerous sets of GCBs were inserted into the machine. The beans were first sorted manually by the evaluators from the NCRDEC. The evaluators were researchers with knowledge and background, obtained through training, in GCB grading. This served as the basis to correctly identify which beans were correctly sorted. To measure the accuracy, the number of correctly identified beans was compared with the total amount of GCBs inserted into the machine. The beans sorted manually were placed into the machine. The machine was tested thrice with different sets of GCBs. The sets of GCBs used for the accuracy tests were the following: Test 1 (T1) – 120 good GCBs; T2 – 120 defective GCBs; T3 – 100 good and 20 defective GCBs; T4 – 20 good and 100 defective GCBs; and T5 – 60 good and 60 defective GCBs. The result of manual sorting was used as the basis for the determination of the accuracy of the machine. The accuracy rate of the GCBs quality sorter was determined using Equation 1.

$$Accuracy\ (\%) = \frac{Number\ of\ correctly\ detected\ beans}{Total\ number\ of\ beans\ input} \times 100\% \qquad (1)$$

where *number of correctly detected GCBs* = (*number of correctly detected good GCBs + number of correctly detected defective GCBs*); *number of correctly detected good beans* = (*number of detected good beans – number of incorrectly detected beans*) and *number of correctly detected defective beans* = (*number of detected defective beans – number of incorrectly detected beans*).

Moreover, the GCBs were re-evaluated/validated through manual sorting by the two researchers from the NCRDEC, who served as evaluators. This was to determine the validity of the findings using the same sets of GCBs used for the accuracy testing. The evaluators have not been informed of the set qualities of the GCBs given to them. The percent validity of the sorted GCBs was determined using Equation 2.

$$Validity\ (\%) = \frac{Number\ of\ correctly\ classified\ GCBs}{Total\ number\ of\ GCB\ samples} \times 100\% \qquad (2)$$

where *number of correctly detected GCBs* = (*number of correctly detected good GCBs + number of correctly detected defective GCBs*); *number of correctly classified GCBs* = (*number of correctly classified good GCBs + number of correctly classified defective GCBs*); *number of correctly classified good GCBs* = (*number of classified good GCBs – number of incorrectly classified GCBs*); and *number of correctly classified defective GCBs* = (*number of classified defective GCBs – number of incorrectly classified GCBs*).

2.7.3 Speed Test

The amount of time was also measured per number of maximum beans that can be inserted into the machine to measure the amount of time required to sort at least 1 kg of GCBs.

2.8 Statistical Analysis

The obtained mean results of percent accuracy and validity were statistically assessed through one-way analysis of variance (ANOVA) at a 5% level of significance using the Statistical Package for the Social Sciences (SPSS) version 25 to determine whether or not there were statistically significant differences in the test trials performed. Furthermore, Tukey's honest significant difference (HSD) test was done to ascertain which specific groups' means were different among the treatments used.

3. Results and Discussion

3.1 Functionality

The training results of the quality identifier neural network are shown in Figure 9. The validation accuracy of the network was set at 81.67% at 50 epochs with a loss of 0.3. This showed that the network was deemed to be accurate within its dataset as the validation data.

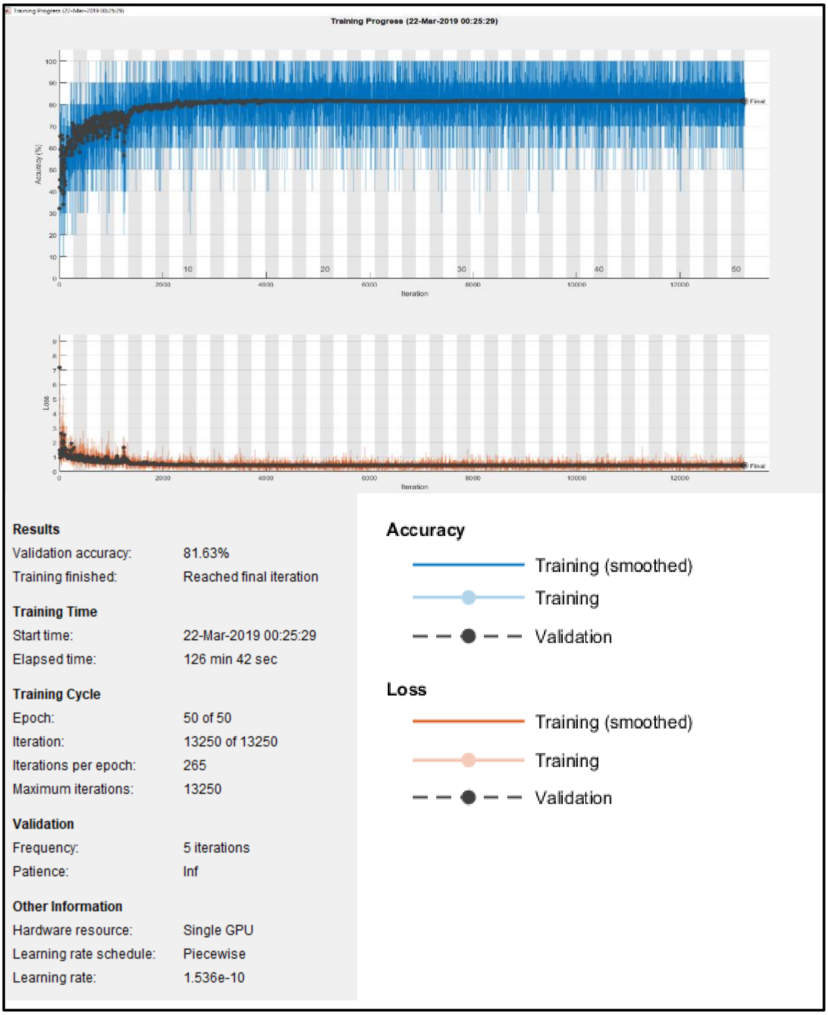

Figure 9. Training progress of the GCB defect identifier

Moreover, in the object detection testing, the classifier detector successfully detected the classification of the beans. In a single image, multiple beans were detected. The YOLOv2 network identified which beans were to be detected out of the GCBs present in the equipment. Figure 10 shows the GCBs inside of the machine, its corresponding boundary box and the image detection label as determined by the network. The classifier network detected that the beans, subjected to testing, were defective since it was smaller than the standard beans based on SCAA (2018) and BAFS (2012) standards. The detected beans were labeled as "smolbean" indicating the size of the beans. Likewise, in Figure 11, it is presented that the highest detection confidence level was 87%. This implied that the program developed for the machine can accurately identify the beans at an 87% confidence level. The process was performed twice for each of the cameras and the detected beans were moved to the defective bean column.

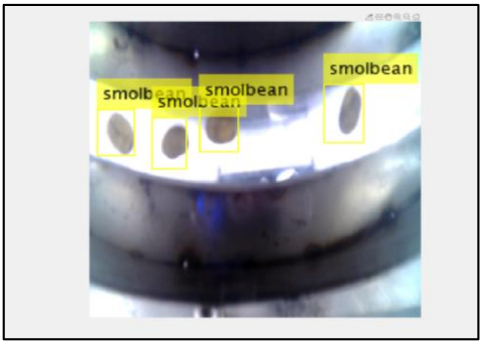

Figure 10. GCBs as classified by the network

Figure 11. Conducted object detection confidence testing for GCBs

Figure 12 shows the prediction output of the MATLAB®. It showed six columns with different values per category. This represented the confidence level of the network in predicting quality. Further, in actual testing presented in Figure 12, the confidence level of detection was established depending on the bean quality category.

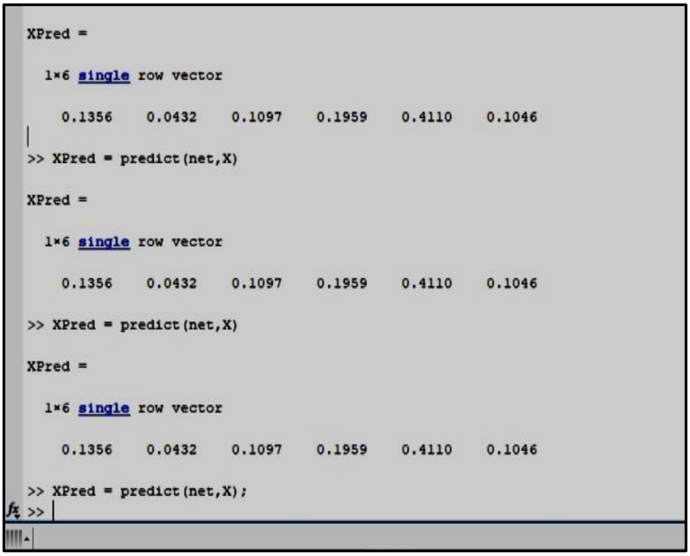

Figure 12. Prediction output of the GCB using MATLAB®

3.2 Accuracy

A series of accuracy tests revealed that the accuracy rate of the machine was found to be at 85, 95, 86.67, 91.67 and 87.50% as shown in Tables 2, 3, 4, 5 and 6, respectively.

Table 2. Accuracy test result with 120 good GCBs (T1)

No. of beans (pcs)	No. of trials			Mean
	Trial 1	Trial 2	Trial 3	
Correctly detected GCBs	101	102	99	101
Incorrectly detected GCBs	19	18	21	19
Total GCBs detected (pcs)	120	120	120	120
Accuracy (%)	84.17	85.00	82.50	85.00

Table 3. Accuracy test result with 120 defective GCBs (T2)

No. of beans (pcs)	No. of trials			Mean
	Trial 1	Trial 2	Trial 3	
Correctly detected GCBs	117	111	114	114
Incorrectly detected GCBs	3	9	6	6
Total GCBs detected	120	120	120	120
Accuracy (%)	97.50	92.50	95.00	95.00

Table 4. Accuracy test result for 100 good and 20 defective GCBs (T3)

No. of beans (pcs)	No. of trials			Mean
	Trial 1	Trial 2	Trial 3	
Correctly detected good GCBs	86	84	82	84
Incorrectly detected good GCBs	14	16	18	16
Correctly detected defective GCBs	20	20	20	20
Incorrectly detected defective GCBs	0	0	0	0
Total GCBs detected	120	120	120	120
Accuracy (%)	88.23	86.67	85.00	86.67

Table 5. Accuracy test result for 20 good and 100 defective GCBs (T4)

No. of beans (pcs)	No. of Trials			Mean
	Trial 1	Trial 2	Trial 3	
Correctly detected defective GCBs	98	95	91	95
Incorrectly detected good GCBs	2	5	9	5
Correctly detected good GCBs	18	14	12	15
Incorrectly detected good GCBs	2	6	8	5
Total GCBs detected	120	120	120	120
Accuracy (%)	94.16	90.83	85.83	91.67

Table 6. Accuracy test result for 60 good and 60 defective GCBs (T5)

No. of beans (pcs)	No. of trials			Mean
	Trial 1	Trial 2	Trial 3	
Correctly detected good GCBs	52	50	49	50
Incorrectly detected good GCBs	8	10	11	10
Correctly detected defective GCBs	57	55	52	55
Incorrectly detected good GCBs	3	5	8	5
Total GCBs detected	120	120	120	120
Accuracy (%)	90.83	87.50	84.17	87.50

Meanwhile, the results of the validation of the accuracy tests performed by two trained researchers are shown in Tables 7-11.

Table 7. Re-evaluation result of the accuracy test of 120 good GCBs (T1)

No. of beans (pcs)	Evaluator 1	Evaluator 2	Mean
Classified good GCBs	119	120	119.50
Classified defective GCBs s	1	0	0.50
Total GCBs classified	120	120	120.00
Validity of the input (%)	99.17	100	99.59

Table 8. Re-evaluation result of the accuracy test for 120 defective GCBs (T2)

No. of beans (pcs)	Evaluator 1	Evaluator 2	Mean
Classified good GCBs	0	0	0.00
Classified defective GCBs	120	120	120.00
Total GCBs classified	120	120	120.00
Validity of the input (%)	100	100	100.00

Table 9. Re-evaluation result of accuracy test for 100 good and 20 defective GCBs (T3)

No. of beans (pcs)	Evaluator 1	Evaluator 2	Mean
Classified good GCBs	84	114	99.00
Classified defective GCBs	36	6	21.00
Total GCBs classified	120	120	120.00
Validity of the input (%)	86.67	83.33	85.00

Table 10. Re-evaluation result of the accuracy test for 20 good and 100 defective GCBs (T4)

No. of beans (pcs)	Evaluator 1	Evaluator 2	Mean
Classified good GCBs	13	13	13.00
Classified defective GCBs	107	107	107.00
Total GCBs classified	120	120	120.00
Validity of the input (%)	88.33	88.33	88.33

Table 11. Re-evaluation result of the accuracy test for 60 good and 60 defective GCBs (T5)

No. of beans (pcs)	Evaluator 1	Evaluator 2	Mean
Classified good GCBs	63	49	56.00
Classified defective GCBs	57	71	64.00
Total GCBs classified	120	120	120.00
Validity of the input (%)	86.67	81.67	84.17

In T1 (120 good GCBs), the sorter presented an accuracy of 85%. On the other hand, in T2 (120 defective GCBs), the machine obtained 95% accuracy – the highest among the five tests performed. For T3 (100 good GCBs + 20 defective GCBs), the total accuracy for the three trials was 86.67%. However, for T4 (20 good GCBs + 100 defective GCBs), the machine yielded an accuracy of 91.67%. With an equal amount of good and defective GCBs (T5: 60 good GCBs + 60 defective GCBs), the machine had an accuracy of 87.5%. Overall, the developed GCB quality sorter obtained an accuracy of 89.17%. Furthermore, in terms of the validity of the detected GCBs based on the re-valuation result performed by trained evaluators, the result showed an overall validity of 91.42%. Table 12 shows the summary of all the accuracy tests performed in the final evaluation and their average accuracies based on their respective trials.

Table 12. Summary of the accuracy test results

Test	*Mean % accuracy	*Mean % validity
T1: 120 good GCBs	85.00[a]	99.59[b]
T2: 120 defective GCBs	95.00[b]	100.00[b]
T3: 100 good GCBs + 20 defective GCBs	86.67[a]	85.00[a]
T4: 20 good GCBs +100 defective GCBs	91.67[ab]	88.33[a]
T5: 60 good GCBs + 60 defective GCBs	87.50[a]	84.17[a]
Average	89.17	91.42

*Means with the same letter are not significantly different at 5% level of significance using Tukey's HSD post-hoc test.

Tables 13 and 14 present the result of the statistical treatment of data obtained from the performance tests conducted. Based on the result, P-values of 0.007 and 0.001 were obtained for the percent accuracy and validity, respectively. The results implied that there were significant differences among the test trials performed on the percent accuracy and validity of the equipment. Moreover, as shown in Table 11, a high percent accuracy of 95% was obtained in T2 (120 defective GCBs) while a high percent validity of the input was attained in T1 (120 good GCBs) and T2 (120 defective GCBs). Validated using Tukey's HSD test at a 5% level of significance, T2 (120 defective GCBs) was significantly different from the other test treatments but somewhat significant with T4 (20 good GCBs +100 defective GCBs) in terms of percent accuracy, while T1 (120 good GCBs) and T2 (120 defective GCBs) was significantly the same but different from the other treatments in terms of percent validity. The results implied that the developed machine can highly detect the presence of defective beans per batch of operation.

Table 13. ANOVA results for the percent accuracy per test treatment

	Sum of squares	df	Mean square	F	*Sig. (P-value)
Between groups	213.013	4	53.253	6.801	0.007
Within groups	78.298	10	7.830		
Total	291.311	14			

*at 5% level of significance

Table 14. ANOVA results for the percent validity per test treatment

	Sum of squares	df	Mean square	F	*Sig. (P-value)
Between groups	487.221	4	121.805	33.059	0.001
Within groups	18.422	5	3.684		
Total	505.643	9			

*at 5% level of significance

3.3 Machine Speed

The machine dispensed and sorted a certain amount of GCBs ranging from one to 15 pieces every 10 s or about 90 GCBs per minute upon computation. The sorting capability of the machine is better than manual sorting since a human can sort about 80 GCBs per minute using both hands (Vincent, 1987). In one revolution, the machine can dispense beans eight times. One revolution was 120-s long with a constant speed of the conveyor plate. The amount of time for sorting 1 kg of GCBs was 2 h and 45 min. The results implied that the machine can sort a large number of GCBs as fast as a human.

4. Conclusion

The study was able to design and construct the algorithm for the controller circuit for the system, conceptualize and fabricate a GCB quality sorter using PID control as the equipment's controller and develop a neural network for the system. The neural network had an accuracy of 85 and 95% for detecting good and defective GCBs, respectively. The results of the preliminary testing of the developed prototype can be used as reference for designing other similar equipment for the same purpose.

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6. References

Backhaus, A., Lachmair, J., Rückert, U., & Seiffert, U. (2012). Hardware accelerated real time classification of hyperspectral imaging data for coffee sorting. Proceedings of the European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, Bruges, Belgium, 627-632.

Banks, M., McFadden, C., & Atkinson, C. (1999). The world encyclopedia of coffee. London: Anness Publishing Limited.

Bureau of Agriculture and Fisheries Standards (BAFS). (2012). PNS/BAFS 01:2012 – Green coffee beans specification. Retrieved from http://www.bafps.da.gov.ph/images/Approved_Philippine_Standards/PNS-BAFS01-2012GreenCoffeeBeansrevised.pdf

Carrillo, E., & Peñaloza, A.A. (2009). Artificial vision to assure coffee-excelso beans quality. Proceedings of the 2009 Euro American Conference on Telematics and Information Systems: New Opportunities to Increase Digital Citizenship, New York, United States, 1-8.

Calvini, R., Ulrice, A., & Amigo, J.M. (2015). Practical comparison of sparse methods for classification of Arabica and Robusta coffee species using near infrared hyperspectral imaging. Chemometrics and Intelligent Laboratory Systems, 146, 503-511. https://doi.org/10.1016/j.chemolab.2015.07.010

Datov, A., & Lin, Y.C. (2019). Classification and grading of green coffee beans in Asia. Retrieved from http://ap.fftc.agnet.org/index.php

de Oliveira, E.M., Leme, D.S., Barbosa, B.H.G., Rodarte, M.P., & Pereira, R.G.F.A. (2015). A computer vision system for coffee beans classification based on computational intelligence techniques. Journal of Food Engineering, 171, 22-27. https://doi.org/10.1016/j.jfoodeng.2015.10.009

Faridah, F., Parikesit, G.O.F., & Ferdiansjah, F. (2011). Coffee bean grade determination based on image parameter. Telkomnika, 9(3), 547-554.

Ferrão, L.F.V., Caixeta, E.T., Pena, G., Zambolim, E.M., Cruz, C.D., Zambolim, L., Ferrão, M.A.G., & Sakiyama, N.S. (2015). New EST–SSR markers of *Coffea arabica*: Transferability and application to studies of molecular characterization and genetic mapping. Molecular Breeding, 35, 31. https://doi.org/10.1007/s11032-015-0247-z

Franca, A.S., Oliveira, L.S., Mendonca, J.C.F., & Silva, X.A. (2005). Physical and chemical attributes of defective crude and roasted coffee beans. Food Chemistry, 90, 89-94. https://doi.org/10.1016/j.foodchem.2004.03.028

Garcia, M., Candelo-Becerra, J.E., & Hoyos, F.E. (2019). Quality and defect inspection of green coffee beans using a computer vision system. Applied Sciences, 9, 4195. https://doi.org/10.3390/app9194195

Giacalone, D., Degn, T.K., Yang, N., Liu, C., Fisk, I., & Münchow, M. (2019). Common roasting defects in coffee: Aroma composition, sensory characterization and consumer perception. Food Quality and Preference, 71, 463-474. https://doi.org/10.1016/j.foodqual.2018.03.009

International Coffee Organization (ICO). (2019). Coffee development report 2019. Growing prosperity – Economic viability as the catalyst for a sustainable coffee sector. Retrieved from http://www.ico.org/documents/cy2019-20/ed-2320e-coffee-development-report.pdf

International Coffee Organization (ICO). (2020). Coffee production data as of July 2020. Retrieved from http://www.ico.org/prices/po-production.pdf

Mancha Agresti, P.D.C., Franca, A.S., Oliveira, L.S., & Augusti, R. (2008). Discrimination between defective and non-defective Brazilian coffee beans by their volatile profile. Food Chemistry, 106, 787-796. https://doi.org/10.1016/j.foodchem.2007.06.019

Pereira, G.V.D.M., Carvalho Neto, D.P., Magalhães D.A.I., Jr., Vásquez, Z.S., Medeiros, A.B.P., Vandenberghe, L.P.S., & Soccol, C.R. (2019). Exploring the impacts of postharvest processing on the aroma formation of coffee beans – A review. Food Chemistry, 272, 441-452. https://doi.org/10.1016/j.foodchem.2018.08.061

Pereira, G.V.D.M., Soccol, V.T., Brar, S.K., Neto, E., & Soccol, C.R. (2017). Microbial ecology and starter culture technology in coffee processing. Critical Reviews in Food Science and Nutrition, 57(13), 2775-2788. https://doi.org/10.1080/10408398.2015.1067759

Pinto, C., Furukawa, J., Fukai, H., & Tamura, S. (2017). Classification of green coffee bean images based on defect types using convolutional neural network (CNN). Proceedings of the International Conference on Advanced Informatics, Concepts, Theory, and Applications (ICAICTA), Denpasar, Indonesia, 1-5.

Ramalakshmi, K., Kubra, R., & Rao, L.J.M. (2007). Physico-chemical characteristics of green coffee: Comparison of graded and defective coffee beans. Journal of Food Science, 72, S-333-S-337. https://doi.org/10.1111/j.1750-3841.2007. 00379.x

Semen, S., Mercan, S., Yayla, M., & Açıkkol, M. (2017). Elemental composition of green coffee and its contribution to dietary intake. Food Chemistry, 215, 92-100. https://doi.org/10.1016/j.foodchem.2016.07.176

Specialty Coffee Association of America [SCAA]. (2018). Coffee standards. A Specialty Coffee Association of America resource. Retrieved from https://static1.squarespace.com/static/584f6bbef5e23149e5522201/t/5d936fa1e29d4d5342049d74/1569943487417/Coffee+Standards-compressed.pdf

Sunarharum, W.B., Yuwono, S.S., Pangestu, N.B.S.W., & Nadhiroh, H. (2018). Physical and sensory quality of Java Arabica green coffee beans. IOP Conference Series: Earth and Environmental Science, 131, 012018. https://doi.org/10.1088/1755-1315/131/1/012018

Vincent, J.C. (1987). Green coffee processing. In: R.J. Clarke & R. Macrae (Eds.), Coffee. Dordrecht, Netherlands: Springer.

Yusmanizar, Setiasih, I.S., Nurjanah, S., Muhaeimin, M., Nurhadi, B., Rosniawaty, S., & Munawar, A.A. (2019). Fast and non-destructive prediction of moisture content and chologenic acid of intact coffee beans using near infrared reflectance spectroscopy. IOP Conference Series: Materials Science and Engineering, 506. 012033. https://doi.org/10.1088/1757-899X/506/1/012033