Volume 4 | Issue 2 | Jul - Dec 2024
ISSN: 2984-9896

CACAO BEANS CLASSIFIER USING CONVOLUTIONAL NEURAL NETWORK (Kakaw-Suri)

Chris Jhon C. Pariñas,
Henry B. Agcaoili
Doddz R. Danao
Jefferson M. Tulauan
Mhyca M. Axalan
Cagayan State University – Carig Campus
Carig sur, Cagayan, Philippines

ABTRACT

This study presents the development of "Kakaw-Suri," a classifier designed to evaluate cacao beans based on their internal characteristics using Convolutional Neural Networks (CNN). The Philippines national standards for cacao bean grading prioritize internal characteristics, typically assessed via the cut test. However, CSU Lasam Cacao Processing Center in Lasam, Cagayan, revealed that local cacao processing centers often rely on external characteristics, overlooking internal defects such as mold, slate, and insect damage. Addressing this gap, the study focuses on classifying cacao beans internally, aligning with national standards to enhance produce quality. Using a Raspberry Pi, C920 Logitech camera, and an LCD screen, the researchers utilized YOLOv5, a CNN model, for training on 469 images. The researchers then developed a custom kiosk to house the components and implemented a GUI. The classifier demonstrated a notable performance, achieving a 94.39% accuracy rate during testing at the Cagayan Valley Cacao Development Center, Isabela State University. Additionally, the system was evaluated by respondents from Lasam, Cagayan, using ISO 25010 and ISO 9241-210 standards, achieving overall mean scores of 4.07 and 4.08, respectively. These results indicate that Kakaw-Suri can reliably classify cacao beans by internal characteristics, ensuring compliance with Philippine national standards and potentially improving the quality and marketability of local cacao produce.

Keywords: *Cacao Classifier, Cacao beans, CNN*

INTRODUCTION

Cacao, Theobroma cacao, which directly signifies "food of the gods" in Greek, is a petite evergreen that grows to a height ranging from 4 to 9 meters. "Cacao," rooted in Mayan language, encompasses both the tree and its product. Cacao stands as the essential ingredient in chocolate production, with no viable substitute. From cacao beans, six intermediate products can be obtained, including cocoa nibs, cocoa liquor (tablea), cocoa cake, cocoa butter, cocoa powder, and chocolate confectionary blocks.[1][2]

Cacao production in the Philippines peaked at 35,000 metric tons (MT) in 1990. A decline in cacao production occurred due to a combination of factors, including the influence of typhoons, pest infestation, diseases, aging trees, and potential genetic deterioration in commonly used varieties, exacerbated by a decrease in the world market price and competition with other plantation crops like banana and palm oil, leading to a shift in planting preferences. Despite this, current Philippine cacao production stands at 9,340.73 metric tons (MT), according to the 2020 figures released by the Philippine Statistical Authority (PSA) [2].

Grading cacao beans is an indispensable process in the cocoa industry, executed to uphold and guarantee the overall quality of the cocoa beans. The cacao beans are sorted by their size and the percentage of defective beans [3]. Cacao graders perform the cut test to determine the defects from within the beans. The cut test is a part in cacao grading used to assess the quality of fermentation and internal health of the cocoa beans. Cacao shall be graded based on the count of defective beans in the cut test [3].

There are different kinds defected beans indicated in the Philippine National Standard of cacao beans specification and grading: broken beans, flat beans, cluster beans, germinated beans, insect-damaged beans, moldy beans, and slaty beans. Traditionally, farmers remove some of these defects by hand like flat beans of which the cotyledons are too thin to be cut to give a surface of cotyledon [3]. New industrial-grade food sorters use optical sorting that are capable of sorting multiple samples at high speeds. However, the high cost associated with these technologies can present challenges for small cacao farmers who may face financial constraints.

Based on recent local studies [4][5][6], deep learning algorithms like Convolutional Neural Network (CNN) and k-Nearest Neighbors (KNN) have been used in classifying these defects based on the external characteristics of the cacao beans. However, some of the defects might be difficult to detect as they might occur within the bean. Insect-damaged beans, characterized by the presence of insects or mites within the internal parts, moldy beans displaying visible mold on their internal parts discernible without magnification, and slaty beans exhibiting a slaty color covering at least half of the surface of the cotyledons exposed during the cut test [7]. Although these studies have successfully classified beans by analyzing their external features, there is still a lack of local study that classifies cacao beans based on their internal characteristics base on Philippine National Standards.

Objectives of the Study

To develop a system that can grade and classify fermented sample beans. Specifically, it aims to:

1. Develop an image kiosk cacao classifier with customized GUI.
2. Develop a system using convolutional neural network to detect different classifications of cacao beans (good, under fermented, white, slaty, moldy, and insect damage).
3. Evaluate the accuracy of the trained model using performance metrics.
4. Assess the system's quality characteristics based on ISO 25010 software quality standards: (1) Functional Suitability, (2) Performance Efficiency, (3) Compatibility, (4) Interaction Capability, (5) Reliability, (6) Security, (7) Maintainability, (8) Flexibility, and (9) Safety.
5. Assess the system's quality characteristics based on ISO 9241:210 Human-centered design for interactive systems: (1) User Experience, (2) Usability, (3) Accessibility, (4) Safety, (5) Sustainability, and (6) Flexibility.

MATERIALS AND METHODS

Research Design

The study employs developmental research, focusing on the systematic study and analysis of materials and facts to establish a well-defined solution for the problem presented. To assess the performance of image processing in cacao bean classifying, a quantitative approach has been used. This involves collecting and analyzing numerical data related to the processing speed and overall system performance.

The methodology for this research follows a sequential process starting with gathering data requirements from respondents, and then designing the cacao kiosk classifier. After this, we collect and validate the dataset necessary for training the model. Images are acquired and pre-processed to extract relevant features, followed by classifying the data. We then proceed to create the physical kiosk and develop the corresponding software and graphical user interface (GUI). The cacao bean classifier's accuracy is tested to ensure reliability. Finally, the system's quality is assessed using ISO 25010 and ISO 9241:210 standards, ensuring comprehensive evaluation and necessary improvements based on feedback.

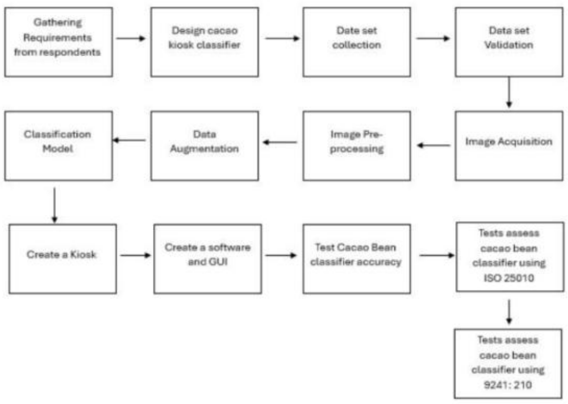


Figure 1: Research Model

Sampling Technique

The study focused on Terry's Cacao Farm and Cagayan State University Cacao Processing Center in Lasam, Cagayan. Respondents selected through purposive sampling, ensuring representation from individuals with expertise in cacao classifying.

Data Gathering Procedure

Gathering Requirements from Respondents

The researchers gathered information regarding cacao farming practices and processing methods by:

- Interviewing farmers at Terrys Cacao Farm (Lasam, Cagayan) and the Cacao Processing Center (CSU LASAM).
- Distributing questionnaires to gather additional perspectives and detailed information from other cacao farmers involved in classification.

Dataset Collection

The researchers provide a detailed overview of the technical specifications and functional requirements for the new system, gathered from the information collected through interviews and questionnaires. Researchers collected 870 samples of cacao bean variety BR25 which is divided into 6 classes: Good Bean, Moldy, Insect Damage, Slaty, Under Fermented, and White Bean for training. There were 870 beans used for training. The following datasets were included; 312 good beans, moldy 228, slaty 90, insect damaged beans 141, white beans 28 and underfermented beans is 71.

Image Acquisition

The researchers used a 5-megapixel macro camera to capture the images of halved cacao bean samples. A gray background instead of white is used to create contrast, making the beans stand out against the background. It also helps control overall brightness, ensuring the beans are captured with the right level of detail and avoiding overexposure issues. A total of 468 images were taken.

Figure 2: 5-megapixel Macro Camera

Dataset Validation

The images taken from the dataset are then categorized and validated by a cacao expert from Cagayan Valley Cacao Development Center to ensure the correctness of the classifications of the dataset.

Figure 3: Validation of Dataset by the cacao expert

Dataset Annotation

The thorough process of annotating raw data with relevant attributes and classifications specific to cacao beans. The validated datasets have been labeled according to its classification provided by the cacao experts. Beans that have optimal fermentation and show no signs of defects have been labeled as good beans, those appearing in violet color have been under-fermented, those with a gray shade like appearance as slaty beans, those show visible mold growth as moldy beans, those that are naturally white have been white beans, and those showing visible signs of insect infestation, such as holes, larvae, have been labeled as insect damage. Every halved bean in the images is labeled using a freeform annotation which allows creating polygons into a more precise shape. The annotated cacao bean sample images were distributed for training, valid, and test set.

Class	Training	Valid	Test
Good Beans	489	97	39
Moldy Beans	314	91	51
Insect-damaged Beans	183	61	38
Slaty Beans	116	48	16
Under-fermented Beans	94	40	9
White Beans	36	20	0
Total	**1,232**	**357**	**153**

Table 1. Training, Valid and Test Set Beam Halves Distribution Count

Image Pre-processing

The pre-processing step have involve resizing all captured cacao bean images to a uniform resolution of 2048x1152 pixels to ensure consistency across the dataset.

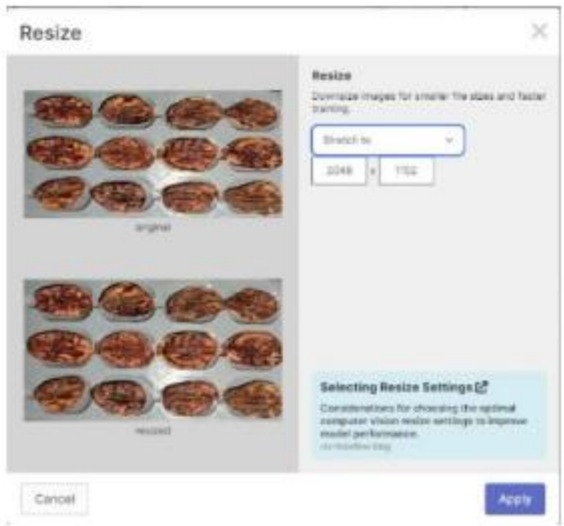


Figure 4: Image Pre-Processing, Resizing

Data Augmentation

This process includes techniques such as rotation, flipping, cropping, and color manipulation applied to cacao bean images. By augmenting the dataset with variations of the original images, researchers can improve the generalization and performance of machine learning models trained on limited data. The researchers used these techniques:

- Horizontal and Vertical Flips
    - Horizontal Flip: Reflect the image along its vertical axis.
    - Vertical Flip: Reflect the image along its horizontal axis.
- 180-Degree Rotation
    - Upside Down: Rotate the image by 180 degrees.
- Rotation
    - Small Angles: Rotate the image randomly between -15° and +15°.
- Shear Transformations
    - Horizontal Shear: Shear the image by an angle between -15° and +15° horizontally.
    - Vertical Shear: Shear the image by an angle between -15° and +15° vertically.

The initial 469 cacao bean images expanded to 1,132 images when the augmentation techniques above were applied.

Classification Model

The architecture of the YOLOv5 consists of three main parts: Backbone, Neck, and Head Backbone, extracts crucial features from the given input image.

The first part, Backbone, extracts crucial features from the given input image. In YOLO-v5, CSPNet s (Cross Stage Partial Networks) are incorporated into Darknet, creating CSPDarknet as its backbone. Compared to the Darknet53 used by YOLO-v3, CSPDarknet has achieved considerable improvement in processing speed with equivalent or even superior detection accuracy (Wang et al. 2020).

The second part, Neck, is primarily employed to generate feature pyramids, which benefit YOLO-v5 in generalizing the object scaling for identifying the same object with different sizes and scales. The final detection is performed in the part of Head. Head generates anchor boxes for feature maps and outputs final output vectors with class probabilities and bounding boxes of detected knots. (Zhu et al. 2020; Xu et al. 2021).

Figure 5: YOLv5 Architecture

Overview of the Image Capture kiosk

This section shows the overview of the Cacao Bean Classifier.

Figure 6: Perspective View of Cacao Bean Sorter

The cacao bean classifier uses components to identify between bean classes. Among its components are the LCD, Rasberry Pi, and Camera. Using this, the classifier can just detect and classify different bean classes according to their visual characteristics.

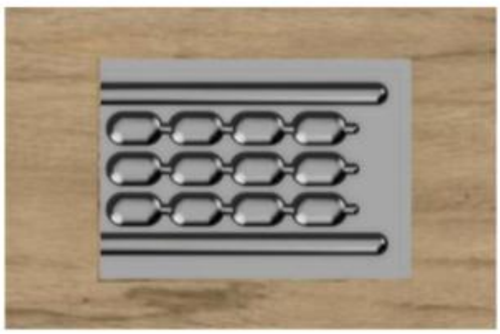


Figure 7: Cacao Slot

The camera view provides CNN a wide range of visual data, which it can analyze and utilize to develop accurate bean recognition capabilities. CNN precisely classifies beans from a single camera POV angle of capture.

Hardware Requirements

This section shows the components of the system and how they interact together to achieve optimal functionality. Both block and schematic diagrams are utilized to provide a better understanding of the system's operation.

Block Diagram

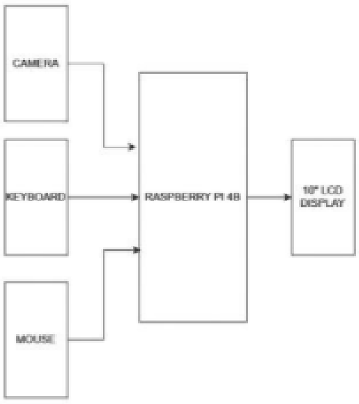


Figure 8: Block Diagram

The block diagram features a Raspberry Pi 4B at its core, receiving input from a keyboard, mouse, and camera. These input devices communicate with the Raspberry Pi, where it processes the inputs and instructs the LCD for output.

Schematic Diagram

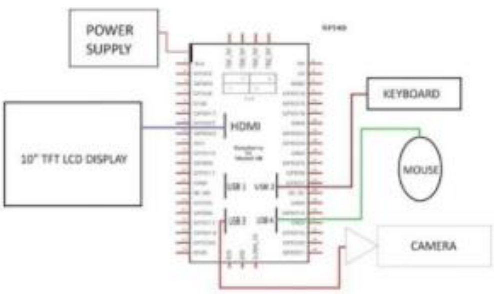


Figure 9: Schematic Diagram

The Raspberry Pi 4B acts as the central control unit and organizes the sorting process. The Camera, connected via the USB port of the control unit, captures high-resolution images of cacao beans, ensuring accurate and detailed image acquisition for classification. There are three input devices: a keyboard, connected via USB, allows users to input commands, and manually continue the classification process when needed; a mouse, also connected via USB, provides a user-friendly way to navigate the GUI and interact with the classifier software; and the camera for capturing images. An LCD display, connected via HDMI, serves as the output device, showing the GUI, results, and real-time data, making the classifier easy to monitor and control. The entire system is powered by a 5V/3A power supply, ensuring stable operation of the Raspberry Pi 4B and its peripherals.

Materials

The cacao bean sorting machine incorporates a set of primary components. The integration of these components is crucial for the singulation, classifying, and sorting process. The primary components include:

HARDWARE COMPONENTS	FUNCTION
 LCD Display 52Pi	LCD enhances the operation's precision and efficiency by providing a user-friendly interface for visualizing and interacting with the controls and data involved in the classification process. -Screen size 10.1 inches -Resolution 1024x600 pixel -Refresh Rate 60Hz
 Raspberry Pi 4 Model B:	As the core processing unit, the Raspberry Pi 4 Model B serves as the brain of the cacao bean classifying machine. It manages data processing, decision-making, and communication with other hardware components.
 Logitech c920 webcam	The camera acts a major part in providing CNN with the visual data required for the accurate classification of the beans. Specifications:
 Filament	3D printing filament is the thermoplastic feedstock for fused deposition modeling 3D printers. There are many types of filaments available with different properties.

Systems Flowchart

The system starts with acquiring and preprocessing an image of the cacao bean, followed by image preprocessing for classification. The beans are then sorted into specific bins in accordance with the classification. The sorted cacao beans are the output.

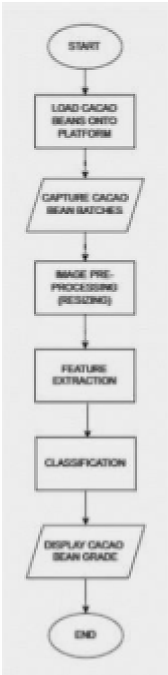


Figure 10: System's Flowchart

Operational Flowchart

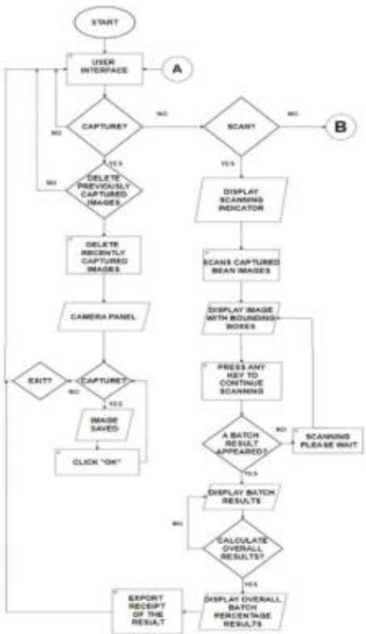


Figure 11: Operational Flowchart (part 1)

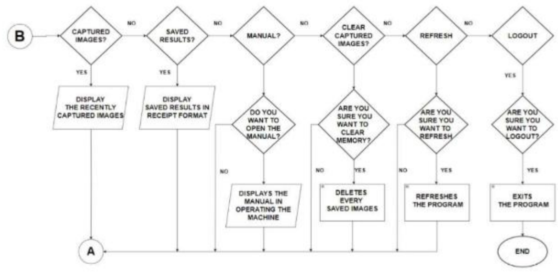


Figure 12: Operational Flowchart (part 2)

Statistical Tool

The researchers used the confusion matrix to evaluate the performance of the system in terms of its accuracy, precision, recall, and F1 score metrics.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TN)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Table 2: Confusion Matrix

TP =True Positive; the number of cocoa beans from the positive class is correctly classified as the positive class.

TN =True Negative; the number of cocoa beans from negative class classified as negative class.

FP =False Positive, the number of cocoa beans from negative class, incorrectly classified as positive.

FN =False Negative; the number of cocoa beans from positive class misclassified as negative class.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%$$

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

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

$$\text{F1 score} = 2 \times \frac{Precision \times Recall}{Precision+Recall}$$

The researchers used ISO 25010 to test the software product quality. ISO 25010 provides a framework for specifying, measuring, and evaluating the quality characteristics of software systems and software products.

5-Point Likert Scale have also be used as a statistical tool to assess the feedback of the respondents to the system. It involves respondents indicating their level of agreement or disagreement with a statement using a scale of five options. The options range from strongly agree to strongly disagree, and are represented numerically as follows:

1	Strongly Disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly Agree

Table 3: Likert Scale

RESULTS AND DISCUSSION

This chapter presents the collected data, the results of the tests conducted to study the system's functionality and accuracy, and the interpretation of the findings. These are presented in the order of the objectives of the study to construct a fully operational Cacao Beans Classifier using Convolutional Neural Network.

Cacao Bean Classifier Kiosk

Figure 13: Front view of the cacao beans classifier

Figure 13 shows the front view of the Cacao Beans Classifier. It shows the inclined LCD where the Graphics User Interface is displayed.

Figure 14: Right-side view of the cacao beans classifier

Figure 14 shows the right-side view of the cacao beans classifier. The side panel is equipped with magnets making it removable for easy access inside the components housing. The elevated platform below is for the camera to have a focused view on the cacao slot.

Figure 15: Back view of the cacao bean classifier

Figure 15 shows the back view of the cacao bean classifier. Hinges were installed in between the platform and top casing for full access on the components inside. Vents are also designed on the top casing for airflow.

Figure 16: Interior view of the system

Figure 16 shows the interior of the system. The Raspberry Pi 4B is powered by 5V DC supply. The 10.1-inch display is connected to the Raspberry Pi 4B via HDMI, and its power connected using USB. The Logitech C920 is connected to the Raspberry Pi through USB. The LED Strip is connected to power.

Cacao Bean Classifier Graphic User Interface

The researchers developed a graphical user interface which contains all the necessary functions for a full working cacao beans classifier. Figure 17 shows the dashboard which contains Capture and Scan buttons. It also includes the Captured Images, Saved Results, Manual, Clear Memory, Refresh, and Logout on the side navigation bar.

Figure 17: Dashboard

Figure 18 shows the camera which allows the user to capture the images of the cacao bean samples that loaded onto the platform.

Figure 18: Capture Image

Figure 19 shows the start the classification process of the saved image/s.

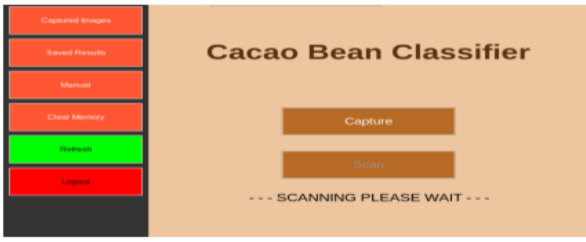


Figure 19: Scanning Captured Images

The scanned images will pop up one by one with bounding boxes that contain their corresponding classes. Press any key to continue the scanning for the succeeding images.

Figure 20: Image Result

Figure 20 21 shows the batch results window will pop up after the last scanned image, showing the class name of every cacao bean in every image scanned. This also includes the total percentages of good beans, under-fermented, white bean, and defected beans per image/batch.

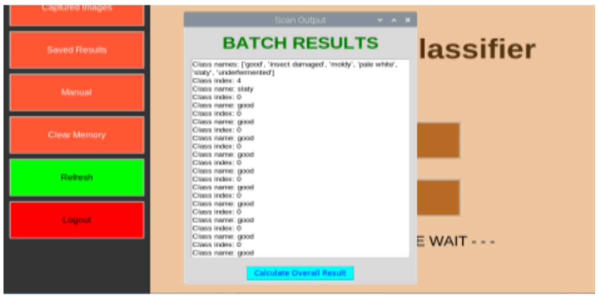


Figure 21: Batch Results

Figure 22 shows the overall results of the classification. It also includes the total bean count, percentages of good, white, under-fermented, and defected beans. The grade of the samples will also be shown with the division of beans in graphical representations.

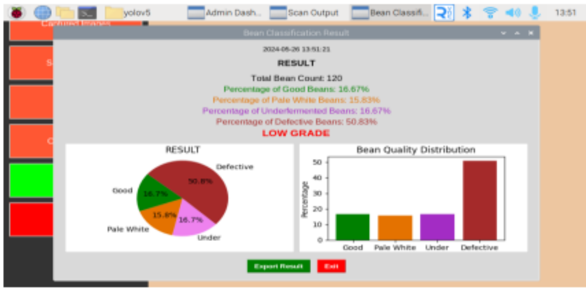


Figure 22: Overall Result

Figure 23 shows the saved results folder where the previously saved results are compiled.

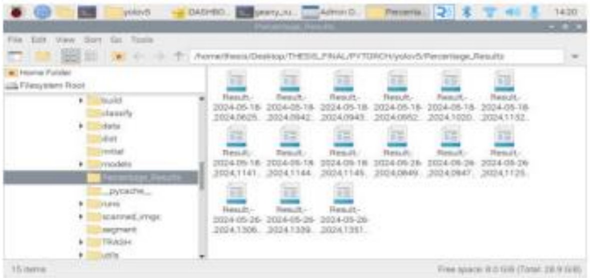


Figure 23: Saved Results

Figure 24 shows the PDF receipt of results which is ready for printing

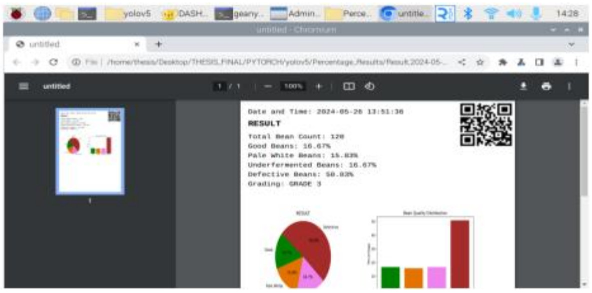


Figure 24: PDF Receipt of Results

Detection of Different Cacao Bean Classification

Initial training

The researchers explored VGG16 and YOLOv5 and the latter was used as it is able to detect and classify multiple cacao beans in an image at once compared to VGG16 which can only classify 1 cacao bean in an image at a time.

The researchers trained their model using Google Colab. They first cloned YOLOv5 Ultranalytics and uploaded the datasets from Roboflow, which were used to label images based on bean classifications. The initial training was set to 100 epochs with a resolution of 416 x 416 to ensure consistent input size. After training, the model's weights were exported as 'best.pt' to serve as the main component of YOLOv5.

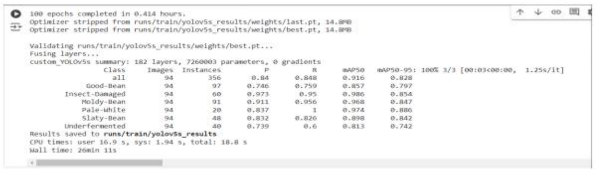
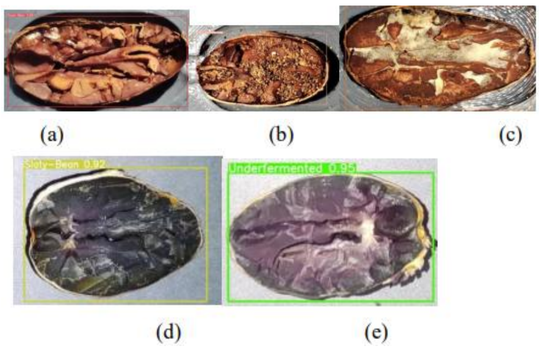


Figure 25: 100 epochs training

The YOLO-V5 model achieved precision (P) of 0.84, recall (R) of 0.848, mean average precision at 50% overlap (mAP50) of 0.916, and mean average precision from 50% to 95% overlap (MAP50-95) of 0.828.



Figures 26: Images of Detected Cacao Beans (a)Good Bean (b)Insectdamaged Bean (c)Moldy Bean (d)Slaty Bean (e)Under-fermented Bean

Cropping of Images in The Dataset

The dataset includes partially captured cacao beans on the edges on some of the images, resulting in a significant loss of accuracy. The researchers cropped out the edges of the images to address the issue. Fine-tuning the datasets is crucial for achieving accurate and precise output with YOLOv5.

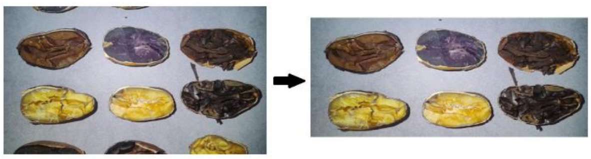
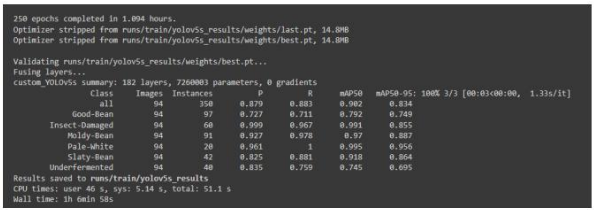


Figure 27: Cropping of the images

Retraining For 250 Epochs

In the second training phase, researchers aimed to achieve a more consistent output by increasing the number of epochs from 100 to 250. This extended training period allowed the model to learn more effectively from the dataset, leading to a closer gap between precision and recall in detecting and classifying the cacao beans. By allowing the model to process the data for more epochs, the researchers ensured that the model had ample opportunity to fine-tune its parameters and better generalize from the training data, resulting in a more accurate and precise performance.



```
250 epochs completed in 1.094 hours.
Optimizer stripped from runs/train/yolov5s_results/weights/last.pt, 14.8MB
Optimizer stripped from runs/train/yolov5s_results/weights/best.pt, 14.8MB

Validating runs/train/yolov5s_results/weights/best.pt...
Fusing layers...
custom_YOLOv5s summary: 182 layers, 7260003 parameters, 0 gradients
            Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 3/3 [00:03<00:00,  1.33s/it]
              all         94        350      0.879      0.883      0.902      0.834
        Good-Bean         94         97      0.727      0.711      0.792      0.749
   Insect-Damaged         94         60      0.999      0.967      0.991      0.855
       Moldy-Bean         94         91      0.927      0.978       0.97      0.887
       Pale-White         94         20      0.961          1      0.995      0.956
       Slaty-Bean         94         42      0.825      0.881      0.918      0.864
   Underfermented         94         40      0.835      0.759      0.745      0.695
Results saved to runs/train/yolov5s_results
CPU times: user 46 s, sys: 5.14 s, total: 51.1 s
Wall time: 1h 6min 58s
```

Figure 28: 250 epochs training

In a dataset of 94 images containing 350 instances, the YOLO-V5 model achieved precision (P) of 0.879, recall (R) of 0.883, mean average precision at 50% overlap (mAP50) of 0.902, and mean average precision from 50% to 95% overlap (MAP50-95) of 0.834.

Evaluation of Test Results

The researchers conducted testing at Cagayan Valley Cacao Development Center, Isabela State University. The cacao expert was asked to determine the classification of the 107 halved cacao bean samples. The same samples were then fed to the Cacao Bean Classifier for capturing and grading. Out of 107 cacao beans, 101 samples were correctly classified.

		GOOD	LATY	MOLDY	INSECT-DAMAGED	UNDER-FERMENTED	WHITE
Expert Defined Class	GOOD	17		0	0	1	0
	SLATY	1	7	0	0	0	2
	MOLDY	0		17	0	0	0
	INSECT-DAMAGED	0		0	16	0	0
	UNDER-FERMENTED	0		1	0	17	0
	WHITE	0		0	0	0	17

Table 4: Confusion Matrix

To determine the precision, recall and f1 score for each class, the following formulas were used.

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

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

$$\text{F1 score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

TP =True Positive; the number of cocoa beans from the positive class is correctly classified as the positive class.

TN =True Negative; the number of cocoa beans from negative class classified as negative class.

FP =False Positive, the number of cocoa beans from negative class, incorrectly classified as positive.

FN =False Negative; the number of cocoa beans from positive class misclassified as negative class.

Class	Precision	Recall	F1 Score
Good	0.944	0.894	0.918
Slaty	0.944	0.85	0.895
Moldy	0.944	1	0.971
Insect-damaged	1	1	1
Under-fermented	0.944	0.944	0.944
White	0.894	1	0.944
Average	**0.945**	**0.948**	**0.945**

Table 5: Precision, Recall, and F1 Score Summary

To determine the Accuracy:

$$\text{Accuracy} = \frac{no.\ of\ correct\ predictions}{total\ no.of\ predictions} \times 100\%$$

$$\text{Accuracy} = \frac{101}{107} \times 100\% = 94.39\%$$

Where: Number of correct predictions is the summation of diagonal values in confusion matrix.

Total no. of predictions is the number of test data.

CSU Lasam Cacao Processing Center and Terry's Cacao Farm Evaluation on the ISO 25010 Software Quality Standards

The system was evaluated by the respondents in Lasam, Cagayan using a 5- point likert scale to determine the extent of software compliance of the developed system with the ISO 25010 Software Quality Assurance Standards in terms of functional suitability, performance efficiency, compatibility, interaction capability, reliability, security, maintainability, flexibility, and safety. The evaluation findings are listed below.

Table 6. Mean Range

Mean Range	Description Interpretation
4.21-5.00	Strongly Agree (Accepted Unconditionally)
3.41-4.20	Agree (Accepted with Minor Condition)
2.61-3.40	Neutral
1.81-2.60	Disagree (Accepted with Major Condition)
1.00-1.80	Strongly Disagree (Reject)

Data were gathered using a 5-point Likert scale to assess participants' perceptions of the developed system's compliance with ISO standards. The scale ranged from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Participants rated how well the system adhered to the ISO 25010 Software Quality Assurance Standards. The table above provides a description of each scale point, which has been used to interpret the mean scores.

Table 7 shows the result of the survey conducted for compliance to ISO 25010 and the following were noted on the specific areas

Functional Suitability

The system is viewed positively, meeting the necessary requirements, and performing reliably, though some minor enhancements could further align it with user expectations and objectives.

Performance Efficiency

The software consistently meets the specified throughput rates for processing tasks within acceptable timeframes. While the software generally performs well and meets the necessary requirements, there are minor conditions or areas for improvement that could further enhance its efficiency and resource utilization, ensuring it fully meets user expectations and specified requirements.

Compatibility

The overall feedback is positive and suggests that the software generally integrates well and communicates effectively with other products and systems, there may be minor conditions or areas for improvement that could enhance its interoperability and performance in shared environments.

Interaction Capability

The overall feedback is positive and suggests that the software is generally userfriendly, easy to learn, and intuitive, there may be minor areas for improvement to further enhance its usability and ensure that users can fully utilize its capabilities without difficulty.

Reliability

The software performs specified functions without encountering faults during normal operation with the overall feedback being positive and suggests that the software is reliable, available, and resilient, there may be minor conditions or areas for improvement that could further enhance its strength and ensure uninterrupted performance.

Security

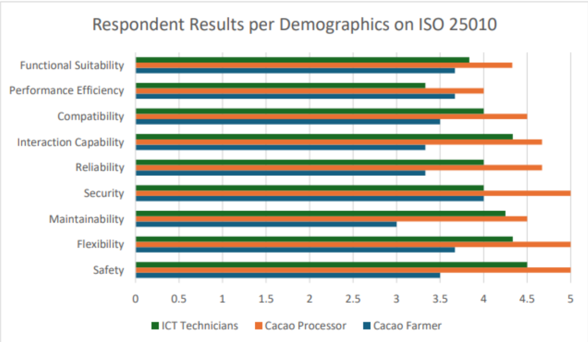
The feedback is very positive, suggesting that the system excels in protecting data integrity and maintaining operations even in the face of malicious attacks, meeting the highest standards of security and resilience.

Maintainability

The software program is structured into discrete components to minimize the impact of changes. Additionally, the product or system can be modified without introducing defects or degrading quality.

Table 7. Overall Summary of the Respondents' Evaluation on ISO 25010 Software Quality Standards

Criteria	Respondents	
	Mean	Description
Functional Suitability	3.92	Agree (Accepted with Minor Condition)
Performance Efficiency	3.58	Agree (Accepted with Minor Condition)
Compatibility	4	Agree (Accepted with Minor Condition)
Interaction Capability	4.17	Agree (Accepted with Minor Condition)
Reliability	4	Agree (Accepted with Minor Condition)
Security	4.25	Strongly Agree (Accepted Unconditionally)
Maintainability	4	Agree (Accepted with Minor Condition)
Flexibility	4.33	Strongly Agree (Accepted Unconditionally)
Safety	4.37	Strongly Agree (Accepted Unconditionally)
Overall Mean	**4.07**	**Agree (Accepted with Minor Condition)**



Graph 1: Respondent Results per Demographic on ISO 25010 (ICT Technicians, Cacao Processor, Cacao Farmer)

Respondents	Overall Mean
ICT Technicians	4.58
Cacao Processor	4.63
Cacao Farmer	3.51

Table 8: Overall Mean per Respondent Demographic on ISO 25010

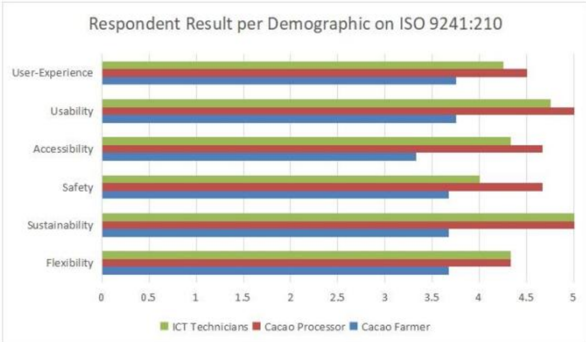
Table 8 shows the overall mean per respondent demographic on ISO 25010, Cacao Processor having the highest mean with 4.63, followed by ICT Technicians with 4.58, and Cacao Farmer having the lowest with 3.51.

CSU Lasam Cacao Processing Center and Terry's Cacao Farm Evaluation on the ISO 9241-210 Ergonomics of Human-System Interaction

The system was evaluated by the respondents in Lasam, Cagayan using a 5- point Likert scale was used to determine the extent of hardware compliance of the developed device with the ISO 9241:210 Ergonomic of human-system interaction standard. This evaluation aimed to measure aspects such as user-experience, usability, accessibility, safety, sustainability, and flexibility. The evaluation findings are listed below.

Table 9: Ergonomics of Human System Interaction

Criteria	Respondents	
	Mean	Description
User-Experience	4	Agree (Accepted with Minor Condition)
Usability	4.37	Strongly Agree (Accepted Unconditionally)
Accessibility	4	Agree (Accepted with Minor Condition)
Safety	3.92	Agree (Accepted with Minor Condition)
Sustainability	4.25	Strongly Agree (Accepted Unconditionally)
Flexibility	3.92	Agree (Accepted with Minor Condition)
Overall Mean	**4.08**	**Agree (Accepted with Minor Condition)**



Graph 2: Respondent Result per Demographic on ISO 9241:210

Respondents	Overall Mean
ICT Technicians	4.44
Cacao Processor	4.7
Cacao Farmer	3.64

Table 10: Overall Mean per Respondent Demographic on ISO 9241:210

Table 10 shows the overall mean per respondent demographic on ISO 9241:210, Cacao Processor having the highest mean with 4.7, followed by ICT Technicians with 4.44, and Cacao Farmer having the lowest with 3.64.

Usability

The overall computed frequency of the device when it comes to usability is both the same, simply means that the device is useful and easy to use.

Efficiency

In testing its efficiency, most of the respondents agreed that the device is showing correct information and data.

Sustainability

The respondents are aware of its sustainability and so far, they agreed that the device can sustain its level of performance.

Portability

The computed frequency proved that the device is easy to transfer to another environment.

User Experience

Based on the result of the data gathered the device is useful to the respondents' productivity. It meets the users expectations in terms of design

Safety

Based on the result of the data gathered the device confine its operation within safe parameters and states when phase with operational hazards.

CONCLUSIONS

Based on the acquired information, the researchers successfully developed a fully functional Cacao Beans Classifier using the YOLOv5 Convolutional Neural Network, integrated into a user-friendly kiosk with essential electronic components. The system demonstrated a notable classification accuracy, distinguishing between various categories of cacao beans with a 94.39% rate during practical testing at the Cagayan Valley Cacao Development Center. Further evaluations based on ISO 25010 and ISO 9241:210 standards confirmed the classifier's functional suitability, performance efficiency, and ergonomic design, with minor conditions noted.

RECOMMENDATIONS

Based on the conclusions of the study, the following are recommended:

1. Use a better camera that can capture images on higher resolution than 1080p.
2. Utilize a faster and newer deep learning algorithm like YOLOv8 for faster calculation.
3. Upgrading the microprocessor from Raspberry Pi 4b to Raspberry Pi 5 will improve the speed and the performance of the cacao beans classifier.
4. Install a battery that can power the cacao beans classifier even in remote areas.
5. Develop a cacao slot for different sizes of cacao beans.
6. Expanding the cacao slot to accommodate about 300 samples of cacao bean in a single batch to ensure that the same beans are not fed repeatedly in the classifier.
7. For security, use marks for images to create identification of the bean samples.
8. Improve the software so that it only uses images taken by the dedicated camera.