# YOLOv8-BASED COMPUTER VISION SYSTEM FOR AUTOMATED CACAO BEAN DEFECT DETECTION AND QUALITY INSPECTION

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***ABSTRACT*** *- Existing quality control methods of cacao beans usually involves manual defect inspection which can be subjective, labor-intensive and expert-dependent. Thus, this study introduces an automated cacao defect detection system using computer vision and the YOLOv8 object detection algorithm. A total of 1,596 images of manually sliced cacao beans were collected from various farms in Misamis Oriental, Philippines. These images were annotated using Roboflow, resized and augmented, and split into training, validation, and testing sets with a 70, 20, and 10 percent ratio. The YOLOv8 model trained for 25 epochs, with hyperparameter tuning and regularization to improve performance. The results showed a high testing accuracy of 95.07%. The precision, recall, and mean Average Precision (mAP50-95) values were 0.9626, 0.9483, and 0.9833, respectively. This suggests that with the developed system, subjectivity and error can be reduced compared to manual inspection. This study presents a practical solution for improving quality assurance in cacao industry, lowering labor costs, and providing foundation for automated postharvest processing systems.*

**Keywords**: *Cacao fruit, computer vision, defect detection, YOLOv8, quality assurance.*

## 1. INTRODUCTION

Cacao (*Theobroma cacao L.*) is a key ingredient in chocolates and various confectionary products. The quality of cacao beans affects its flavor, texture, and overall product quality. Hence, post-harvest quality assessment of cacao beans before it reaches commercial production is critical in attaining high and consistent quality of cacao-based products, thereby avoiding economic losses by farmers and manufacturers and dissatisfaction of customers.

Normally, cacao beans undergo a sorting process to remove those with physical deformities [1]. However, in recent times, cacao bean quality inspection is conducted through manual vision sorting. This traditional process can be arduous, time consuming and requires an expert workforce. Given that this method is visual in nature, it may provide inaccurate results especially when dealing with large volume of beans, as human judgment can be subjective [2, 3]. More so, the dearth of labor force, especially with the need of experts in cacao bean defect identification, may affect this industry in the long run. Therefore, improving the post-harvest quality inspection of cacao beans has never been more important.

Automation has been increasingly introduced in various agriculture industries, including cacao. For instance, the automated cacao pod splitting and cacao bean extraction technologies [4, 5]. Nonetheless, integrating defective bean detection in these technologies remain a challenge. A single defective bean undetected and proceeds to succeeding stages can affect overall quality of the harvest. Hence, an automated computer-vision system to detect defective beans can be the future. Implementing defect detection prior to bean extraction through image processing techniques could significantly improve sorting accuracy.

Image processing has been widely utilized across various fields for real- time applications such as autonomous vehicles and medical imaging [6, 7]. Recently, image processing has been adopted in agriculture for crop monitoring, fruit detection, disease identification, and quality assessment [8-11]. In the context of cocoa production, integrating image processing could transform quality assessment by ensuring that only high-quality beans are selected for further processing. This advancement would not only enhance manufacturing efficiency but also improve the overall quality of cocoa-based products.

Numerous studies have explored computer vision in agricultural quality inspection; however, there are limited studies focusing on automated defect detection of freshly opened cacao beans particularly using locally sourced Philippine cacao. Some studies exist but they focus on quality evaluation of post-fermentation rather than real-time visual inspection immediately after pod opening [2], [12]-[14]. Another study involves object detection for cacao bean defects but for batch detection [3] and other studies about cacao are existing but focus on cocoa pod disease and detection and classification of depodded cocoa beans, respectively [15], [16], not the freshly opened cacao pod, which is the focus of this study. This gap presents an opportunity to develop computer vision model tailored for early-stage quality assessment, particularly freshly opened or cut cacao pod that can support automated harvesting and post-harvest operations.

Hence, this study develops a computer vision-based defect detection system for freshly opened cacao beans using the YOLOv8 object detection algorithm. Images of manually sliced cacao beans were collected and annotated to train and evaluate the proposed model in identifying defective and non-defective beans. The developed system is limited to model training and evaluation only and is intended as a precursor to an integrated intelligent defect detection into automated cacao pod splitting and bean extraction machines in separate future studies. By providing rapid, objective, and accurate quality assessment, the developed system has the potential to improve post-harvest quality control, reduce dependence on manual inspection, and contribute to the modernization and sustainability of the Philippine cacao industry.

## 2. METHODOLOGY

The development of a computer vision-based system for detecting defects in manually opened cacao fruits involves the following stages: data collection and preparation, model training, and evaluation, discussed in detail below.

### 2.1 Data Collection and Preparation

A total of 1,596 images of freshly opened cacao fruits with beans still in their pods were collected from several cacao farms in Misamis Oriental, Philippines. Images captured via smartphone represented both healthy and defective cacao beans under varying lighting conditions, distance, viewing angles and background. The dataset was manually annotated using Roboflow [17]. Figure 1 shows a sample of dataset annotated in Roboflow, where both non-defective and defective beans (exhibiting discoloration, mold, hollowing) were labeled accordingly. To prepare for model training, the images were resized to 640 × 640 pixels and augmented through horizontal flipping and HSV color adjustments. The dataset was divided into 70% training, 20% validation, and 10% testing.

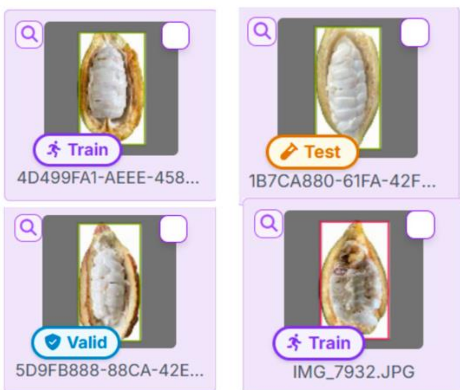


**Figure 1. Roboflow Dataset Overview**

2.2 Model Training

The annotated dataset was used to train a YOLOv8 object detection model for defect identification. YOLOv8 is chosen due to its real-time object detection capabilities and high accuracy [15, 18]. Moreover, the YOLOv8 model's architecture allows it to process images quickly, achieving inference speeds that are critical for time-sensitive applications such as agricultural harvesting. In addition, its ability to maintain high precision and recall rates further confirms its effectiveness in real-world scenarios, where accurate defect detection is essential. Additionally, ongoing research into enhancing YOLOv8's capabilities continues to explore advanced techniques, ensuring that it remains at the forefront of object detection technology in various domains.

Training was performed for 25 epochs, with the validation set used to monitor performance and reduce overfitting. During each epoch, the model processes the training data, adjusting its internal parameters based on feedback received from its predictions compared to the actual annotations. This iterative learning enables the model to identify patterns and features associated with defects in cacao fruits. The model is trained using the training dataset, while a validation set is utilized to tune parameters and avoid overfitting. Hyperparameter tuning was conducted to optimize detection accuracy and improve model generalization.

2.3 Model Evaluation

Approximately 100 images of manually opened defective and non-defective cacao beans sourced from multiple cacao farms were collected and prepared to serve as an independent test dataset. The optimized model discussed in 2.2 is used to run this test dataset. Performance was assessed using accuracy, precision, recall, and F1-score by comparing the model's predictions to the actual labels in the test dataset. This evaluation measured the model's capacity to correctly classify defective and non-defective cacao beans.

## 3. RESULTS AND DISCUSSION

3.1 Model Training Performance

The YOLOv8 model was successfully trained using the annotated dataset of manually opened cacao fruits.

Figure 2 shows the four metrics evaluating model performance over 25 epochs. Each plot shows the evolution of the metrics values namely precision, recall, mAP50, and mAP5095.

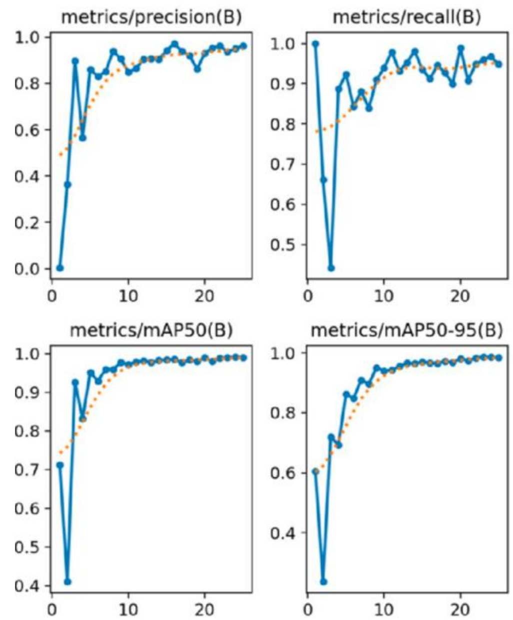


**Figure 2. Performance Metrics**

As can be seen, the precision metric starts lower in the initial epochs, then rapidly increases and stabilizes around 0.96261. This performance indicates that as training progresses, the model becomes more accurate in identifying true positives among predicted positives.

On the other hand, Recall metric remains consistently high from the start then stabilizes around 0.94826 throughout the training process. This implies that the model is highly effective at identifying true positives among all actual positives, demonstrating strong sensitivity and reliability in its detection capabilities.

The mean Average Precision (mAP) at an IoU threshold of 0.5 progresses rapidly from a lower starting point, until it reaches 0.98982. This indicates that the model becomes highly accurate in detecting objects, achieving a strong overlap between predicted and actual bounding boxes.

Lastly, the mAP50-95 metric, which averages precision across IoU thresholds from 0.5 to 0.95, steadily increases and peaks at 0.98332. This indicates that the accuracy of the model improves over a range of thresholds, albeit stricter IoU levels.

Using the testing dataset, the accuracy of the system was evaluated by manually tracking the True Positive, False

Positive, True Negative, False Negative of the detected objects.

3.2 Defect Detection Performance

The trained model demonstrated high accuracy in distinguishing defective and non-defective cacao fruits, producing an overall classification accuracy of 95.07% (see Table 1). The model correctly identified 104 healthy and 33 defective cacao samples, with only eight false positives and one false negative recorded. Defective cacao samples achieved a classification accuracy of 97.06%, while healthy samples achieved 92.86%.

**Table 1 Testing Dataset Accuracy**

| Prediction | Actual "Good" | Actual "Bad" | Total | Accuracy (%) |
|---|---|---|---|---|
| Predicted "Good" | TP =104 | FP =8 | 112 | 92.86% |
| Predicted "Bad" | FN = 1 | TN=33 | 34 | 97.06% |
| Total | 105 | 41 | 137 | 95.07% |

These results indicate that the proposed approach can reliably detect visible defects such as discoloration, mold, and damaged beans. The higher accuracy for defective samples is particularly advantageous in quality assurance because minimizing defective beans entering the production process is more critical than occasional rejection of healthy beans.

The achieved accuracy is comparable with previous computer vision studies on cacao quality assessment, which reported classification accuracies ranging from 93% to 98%, demonstrating the effectiveness of deep learning techniques for automated agricultural inspection.

Figure 3 shows sample results of cacao fruit classification as "Good" or "Bad", with corresponding confidence levels that reflect the model's strong accuracy in identifying high quality and defective cacao, respectively. This demonstrate that the model effectively distinguishes between good and bad quality cacao fruits, as evidenced by the varying confidence levels associated with each classification. Overall, this analysis of the annotated images and their confidence levels provides valuable insights into the performance of the computer vision system during testing.

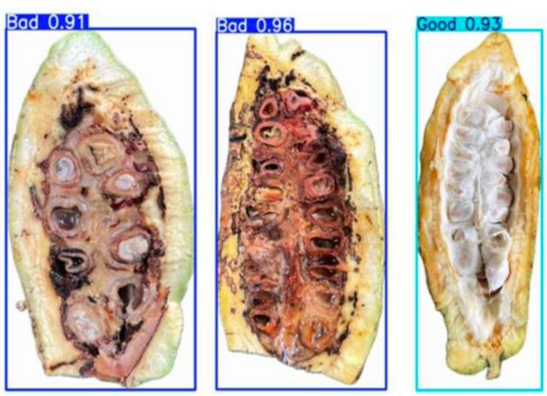


**Figure 3. Sample results of cacao fruit classification with confidence levels**

## 4. Conclusions and Recommendation

This study successfully shows that the image processing algorithm demonstrates an accurate detection rate for defects in manually cut cacao beans, achieving an accuracy of approximately 95% in identifying defective versus non-defective samples. The adoption of computer vision into quality inspection of cacao beans offers a huge advantage over traditional manual sorting and inspection by providing fast and non-subjective evaluation of cacao beans quality at the same time reducing reliance to skilled manpower.

A future study may involve incorporating the developed system in an automated cacao slicing and depodding machine. The dataset may be expanded by including images from a wider range of cacao bean varieties and defect types. An investigation of the impact of humidity and temperature on the quality of cacao beans and the effectiveness of the detection system may also be conducted. Adjusting the system to account for these factors could lead to more enhanced results.

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