Image-Based Analysis and Optimization of Physical Defect Classification in Dried Cacao Beans (Theobroma cacao L.)

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Image-Based Analysis and Optimization of Physical Defect Classification in Dried Cacao Beans (*Theobroma cacao* L.*)*

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Abstract: *This study developed an image-based classification system for dried cacao beans using the YOLOv8n deep learning model to automate defect detection and improve post-harvest quality control. Manual sorting is often slow and inconsistent; this system aims to enhance accuracy and efficiency by identifying seven categories of beans: moldy, cracked, insect-infected, flat, good, germinated, and clustered. A dataset of 1,015 annotated samples was used to train the model, with image labeling conducted via CVAT and augmentation applied using Albumentations. The third training, consisting of 100 epoch or training cycles, produced the best model performance, achieving a training accuracy of 82.87%, 88.6% precision, 91.5% recall, 95.9% mAP@0.5, and 77.1% mAP@0.5–0.95. Real-time testing yielded an overall accuracy of 83.51% across various test configurations. The system reliably classifies defective and good beans in real-time, demonstrating the viability of deep learning and computer vision as practical tools for modernizing cacao quality assessment.*

Keywords: Cacao beans; Deep learning; YOLOv8; Image Classification, Defect Detection.

1. INTRODUCTION

Cacao beans are essential in making chocolate and other products. In the Philippines, cacao is a growing industry, especially in Mindanao [1]. However, sorting dried cacao beans is still done manually, which takes time, effort, and often leads to errors. Defective beans—such as moldy, cracked, insect-infected, flat, germinated, or clustered—can affect product quality and farmer income [2][3][6].
To solve this, the study developed an image-based system using deep learning, specifically the YOLOv8 object detection and a Convolutional Neural Network (CNN) model. By training the model on images of cacao beans, it can classify beans as good or defective based on visible features like mold or cracks. This helps improve accuracy and speed during post-harvest sorting. This research focuses on the dried Trinitario cacao variety, the most common in the country [4][5][8].
The model was trained using cloud-based tools and machine learning libraries, allowing fast and scalable development [7]. The significance of this study was to support farmers and processors by reducing manual labor, improving consistency, and increasing quality control. The study also contributes to agricultural technology by showing how AI can be used for real-world farming challenges, especially in improving cacao production in the Philippines.

2. SUMMARY OF RELATED LITERATURE

The table below shows the comparison between related literature and this work.

Table 1. Summary of Related Literature

Literature	Parameters									
	A	B	C	D	E	F	G	H	I	J
[9]	✓	✓	✓	✓	✓	x	x	x	x	x
[10]	✓	✓	✓	✓	x	x	x	x	x	x
[11]	✓	✓	✓	✓	x	x	x	x	x	x
[12]	✓	✓	✓	✓	x	x	x	x	x	x
[13]	x	✓	✓	x	✓	✓	x	x	x	x
[14]	✓	✓	✓	x	x	x	x	x	x	x
This Study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: A-Cacao Bean, B-Image-based, C-Good, D-Moldy, E-Cracked, F-Insect Infected, G-Flat, H-Germinated, I-Clustered, J-CNN

In this study, the researchers propose an Image-Based Classification to improve the quality control of cacao beans by determining if each bean was good or defective. To achieve this, a Convolutional Neural Network (CNN)'s architecture, You Only Look Once (YOLO), was used to analyze images of the cacao beans, identifying key features that indicate their quality. This approach aims to make the quality control process more efficient and accurate, ultimately helping producers select only the best cacao beans for chocolate and other products.

3. METHODOLOGY

This study followed a structured approach involving data preparation, image annotation, model training, performance evaluation, and real-time testing. The goal was to develop a reliable deep learning system capable of classifying dried cacao beans based on visible physical defects.

3.1 Data Collection and Annotation

The dried cacao beans was classified first at the City Agricultural Office together with the Department of Trade and Industry (DTI). Images were captured using a digital camera, producing 667 photos of cacao beans. These contained 1,015 annotated instances using CVAT, classified into: moldy, cracked, insect-infected, flat, good, germinated, and cluster.

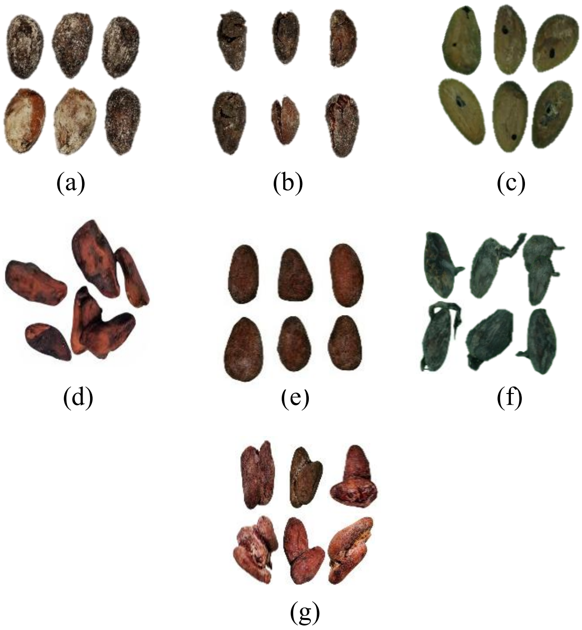

Fig. 1. Dried Cacao Bean Samples. (a) Moldy (b) Craked (c) Insect-Infected (d) Flat (e) Good (f) Germinated (f) Cluster

3.2 Data Augmentation

To improve the model's ability to generalize, image augmentation was applied using the Albumentations library. Augmentation techniques included horizontal and vertical flips, brightness and contrast adjustment, Gaussian noise, and slight rotations. This process increased the dataset's variability and helped the model learn to recognize defects under different image conditions.

3.3 Model Architecture and Training

The study used YOLOv8n, a simple and fast version of a Convolutional Neural Network (CNN), to train a system that can tell the difference between good and defective cacao beans. YOLOv8n was chosen because it works quickly and still gives good results. The training was conducted using Google Colab Pro with GPU acceleration. The dataset was split into training and validation sets using an 80:20 ratio. Three training sessions were carried out with 50, 75, and 100 epochs, respectively.
The model configuration included a batch size of 16, image resolution set to 640×640 pixels, and a learning rate of 0.001. The loss function was based on YOLO's standard object detection loss, which includes classification, localization, and objectness components. Throughout training, checkpoints and logs were generated to track learning progress and model performance.

3.4 Overall System

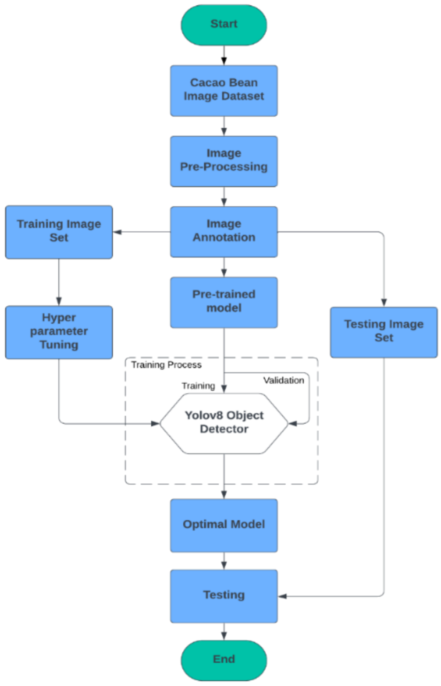

Fig. 2. System Flowchart

The system flowchart outlines the step-by-step process followed to develop a cacao bean detection model using the YOLOv8 algorithm. The process began with collecting a dataset of cacao bean images. These images were then pre-processed to enhance their quality and ensure they were suitable for the next stages. Following pre-processing, annotation was performed to label the cacao beans within each image. The annotated dataset was then split into two parts: a training set and a testing set.
The training set was used to train the model, starting with a pre-trained YOLOv8 model to speed up the process and improve accuracy. Hyperparameter tuning was carried out to optimize the model's performance. During training, validation was conducted to monitor and improve accuracy. Once training was complete, the best-performing version of the model was selected.
Finally, the selected model was evaluated testing set to assess its ability to detect cacao beans in new, unseen images. After successful testing, the final model was deemed ready for deployment. This structured workflow ensured the development of an accurate and reliable object detection model.

3.5 System Algorithm

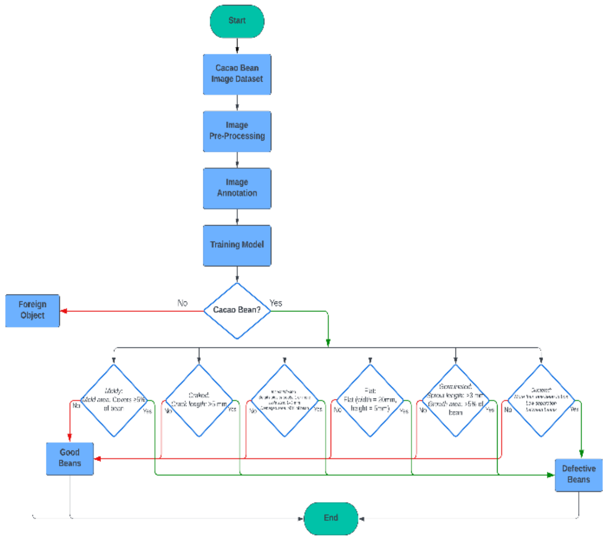

Fig. 3. System Algorithm

The study implemented a parallel defect detection approach for cacao bean classification using a YOLOv8-based deep learning model. The process began with the collection of a cacao bean image dataset, followed by pre-processing steps such as resizing and normalization. Images were then annotated into seven categories: moldy, cracked, insect-infected, flat, germinated, clustered, and good. The model was trained using annotated data and later deployed for real-time image detection. A parallel decision-making structure was adopted to evaluate multiple quality parameters simultaneously. If any single parameter—such as mold coverage ≥5%, cracks >5 mm, insect holes, flatness, germination, or clustering—was detected, the bean was classified as defective. If none of the defects were found, the bean was labeled as good. Non-cacao objects were filtered out as foreign objects. This process enabled efficient multi-defect detection and classification in a streamlined and automated process.

3.6 Evaluation Metrics

After each training session, the model was evaluated using standard metrics: accuracy, precision, recall, F1-score, and mean Average Precision (mAP). Two levels of mAP were recorded: mAP@0.5 and mAP@0.5–0.95. Confusion matrices were generated to analyze misclassifications across classes. Precision-recall curves and training loss graphs were also used to assess training behavior and convergence.

3.7 Real-Time Testing

A real-time testing system was developed using Python and PyCharm. The trained model was loaded into a script to access the camera feed. As beans were placed under the camera, the system detected and classified each one in real time. A total of 849 beans were tested, and the results were manually verified. Three class test categories were used:

- Single-Class Test: 7 sets, each with 50 beans
- Binary-Class Test: Pairs of good vs. defect (e.g., good vs. moldy)
- Multi-Class Test: Equal/unequal distribution of all 7 classes

The real-time testing aimed to simulate actual post-harvest usage and measure practical performance.

3.8 Real-Time Testing vs Manual Human Classification

In this study, both real-time and manual human classification used a consistent testing setup to allow fair comparison. Real-time testing employed a YOLOv8n-based system with a camera that processed live cacao bean images under stable indoor lighting. Beans were tested individually using single-, binary-, and multi-class setups. Manual classification took place at a cacao farm in Butuan City, where a farmer sorted beans by visual inspection under natural light. For both methods, the number of beans, correct classifications, and accuracy were recorded, enabling a clear evaluation of their performance under similar conditions.

4. RESULTS AND DISCUSSION

4.1 Summary of Training Results

To evaluate the performance of the YOLOv8-based cacao bean classification model, three training configurations were executed: 50, 75, and 100 epochs. Each training cycle was assessed using four core evaluation metrics—accuracy, precision, recall, and mean Average Precision at 0.5 Intersection over Union (mAP@0.5). These metrics reflect the model's overall classification effectiveness and its ability to correctly localize and identify beans from different classes.

Table 2. Model Performance Metrics

Model Version	Accuracy (%)	Precision (%)	Recall (%)	mAP@0.5 (%)
50 Epochs	75.62	81.3	83.1	89.0
75 Epochs	79.34	85.7	88.2	93.5
100 Epochs	**82.87**	**88.6**	**91.5**	**95.9**

As shown in Table 1, performance steadily improved with longer training durations. The model trained for 100 epochs achieved the highest overall scores across all evaluation criteria. It attained an accuracy of 82.87%, meaning it correctly classified approximately 83 out of every 100 cacao bean samples. Furthermore, the precision rate of 88.6% demonstrated the model's reliability in making confident predictions with fewer false positives, while the recall score of 91.5% reflected its strong ability to detect relevant instances across all classes, including more visually subtle defects. The mAP@0.5 of 95.9% confirmed a high-quality bounding box prediction across a variety of test images.

This model iteration also showed strong detection performance for both "good" beans, which are critical for export standards, and "clustered" beans, which were previously difficult to detect in early experiments. The improvements can be attributed to a larger and more diverse training dataset, optimization of hyperparameters, and better convergence achieved by extending the training duration to 100 epochs.

4.2 Training Loss Analysis

To further evaluate the learning dynamics of the YOLOv8 model, three core loss values were monitored:

Box Loss, Class Loss (Cls Loss), and Distribution Focal Loss (DFL Loss). These loss values provide insight into how well the model learns object localization, classification, and distribution alignment during training. The comparison across the 50-, 75-, and 100-epoch training runs is shown in Table 2.

Table 3. Loss Training Results.

Training Version	Epoch	Box Loss	Cls Loss	DFL Loss
Training 01	50	0.5982	0.5041	0.9464
Training 02	75	0.5178	0.4469	0.8914
Training 03	100	0.4912	0.4341	0.8783

The results indicate that all three loss components decreased consistently as the number of epochs increased. Box Loss, which measures the model's ability to predict accurate bounding boxes, dropped from 0.5982 to 0.4912, reflecting improved spatial localization. Class Loss similarly declined, indicating that the model became better at classifying beans into their respective categories. The DFL Loss, associated with refining the bounding box regression outputs using probability distributions, also showed notable reduction.

The combined reduction in loss values confirms that the model benefited from extended training. This led to better generalization during testing and a more stable learning process. Notably, the drop in class loss highlights how the model became more proficient at distinguishing between visually similar defects like flat vs. clustered or cracked vs. moldy beans—categories that previously contributed to misclassifications. These training improvements directly contributed to better real-time performance and higher detection confidence, which are further analyzed in the following sections.

4.3 F1-Confidence Curve

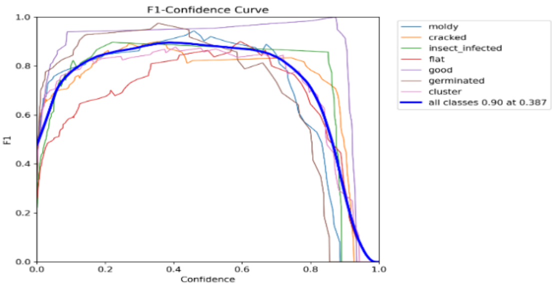

Fig. 4. F1-Confidence Curve

To analyze the relationship between the model's confidence in predictions and its effectiveness, an F1-Confidence Curve was generated. This curve shows how the F1 score varies as the confidence threshold for class predictions is adjusted. Each colored line represents the trend for a specific class, while the bold blue line indicates the average F1 score across all classes.

The curve reveals that as the confidence level increases, the F1 score initially rises, reaching a peak value of 0.90 at a confidence threshold of 0.421. This point represents the optimal trade-off between precision (minimizing false positives) and recall (minimizing false negatives). Beyond this threshold, the F1 score begins to decline slightly, likely due to over-filtering, where fewer beans are detected as confidence demands become too strict.This analysis is crucial in practical deployment, where choosing an optimal confidence level directly affects performance. Based on this result, setting the confidence threshold around 0.42 ensures the highest detection balance.

4.4 Precision-Recall (PR) Curve

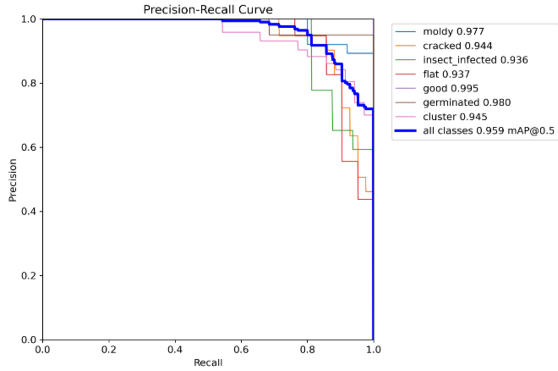

Fig. 5. PR Curve

The Precision-Recall Curve provides a class-wise visualization of the model's trade-off between precision and recall over varying thresholds. Each curve illustrates how well the model can correctly detect beans of a particular class while avoiding false classifications. The thick blue curve represents the macro-average across all classes.

Most classes, including "good" and "germinated", demonstrated high and stable PR curves, signifying consistent detection performance. The overall mAP@0.5 was 95.9%, reinforcing that the model was highly capable of distinguishing between classes, even those with overlapping visual features. The large area under the PR curves reflects both strong precision and high recall, confirming the model's reliability across different confidence levels.

4.5. Real-Time Testing and Accuracy of the Model

To evaluate deployment feasibility, the model was tested in a real-time setup using live camera input. The best-performing model (best.pt, trained for 100 epochs) was loaded via a custom PyCharm interface, where a digital camera was mounted above the cacao beans.

The model processed live input, made predictions in real time, and displayed bounding boxes with class labels. The system performed smoothly, with minimal latency. Good and defective beans were accurately identified, provided they were not overlapping or partially occluded. However, challenges were observed when beans were clustered together or affected by poor lighting. Despite these issues, the model maintained robust inference speed and consistent predictions, highlighting its potential for industrial sorting applications.

4.6 Single-Class Results

Single-class tests evaluated the model's ability to correctly classify beans when only one class was present per test run. This isolated test format helped assess class-specific recognition accuracy.

Table 4. Single-Class Test Results

Test Code	Composition	Beans Tested	Correct	Accuracy (%)
T1-GDCB	Good	50	46	92.00
T2-MDCB	Moldy	50	43	86.00
T3-CRDCB	Cracked	50	41	82.00
T4-IDCB	Insect-infected	50	39	78.00
T5-FDCB	Flat	50	36	72.00
T6-GRDCB	Germinated	50	44	88.00
T7-CLDCB	Clustered	50	40	80.00
Total		350	289	**82.57**

The model showed its highest performance with Good beans (92%), followed by Germinated (88%) and Moldy (86%). Lower accuracies were seen with Flat beans (72%), likely due to subtle texture differences that resemble normal beans. This test confirmed that the model can confidently classify beans in controlled single-class scenarios.

4.7 Binary-Class Test Results

Binary tests mimicked realistic sorting conditions by combining Good beans with one defective class per test. This format simulated export sorting, where a key objective is to separate good beans from all defective types.

Table 5. Binary-Class Test Results

Test Code	Composition	Beans Tested	Correct	Accuracy (%)
T8-GD-MD	25 Good, 25 Moldy	50	45	90.00
T9-GD-CR	25 Good, 25 Cracked	50	44	88.00
T10-GD-ID	25 Good, 25 Insect-infected	50	44	88.00
T11-GD-FL	25 Good, 25 Flat	50	40	80.00
T12-GD-GR	25 Good, 25 Germinated	50	39	78.00
T13-GD-CL	25 Good, 25 Clustered	50	43	86.00
T14-25G25D	25 Good, 25 Mixed Defective	50	40	80.00
Total		350	295	**84.29**

The highest accuracy occurred in Good vs. Moldy (90%), while Good vs. Germinated (78%) showed the most confusion. These results indicate the classifier's strong potential for use in binary sorting tasks, with consistent performance across multiple pairings.

4.8 Multi-Class Balanced Test Results

Multi-class tests presented the most realistic and complex environment by including multiple bean types in balanced proportions.

Table 6. Multi-Class Balanced Test Results

Test Code	Composition	Beans Tested	Correct	Accuracy (%)
T15-MC1	7 classes: ~7 beans each	49	42	85.71
T16-MC2	8 per defective class, 2 good	50	39	78.00
T17-MC3	14 good, 6 per each of 6 defective classes	50	44	88.00
Total		149	125	**83.89**

The system excelled in T17 (88%), where Good beans were more frequent. The lowest score in T16 (78%) highlights difficulties when defective classes dominate. These findings suggest that the classifier is generally robust in mixed environments but can still benefit from improved separation between closely related defect types.

4.9 Overall Accuracy of All test Results

To summarize all evaluation modes (single, binary, and multi-class), the overall real-time accuracy was computed:

Table 7. Overall Accuracy across All Test Results.

Test Category	Total Beans Tested	Correct Predictions	Accuracy (%)
Single-Class Tests	350	289	82.57
Binary-Class Tests	350	295	84.29
Multi-Class Tests	149	125	83.89
Overall Total	**849**	**709**	**83.51**

These results demonstrate that the model maintains consistent performance across diverse classification conditions, with an overall real-time accuracy of 83.51%. This confirms its readiness for deployment in cacao bean inspection, while pointing to areas such as defect overlap where future optimization could improve results further.

4.10 Confusion Matrix Analysis and System Implications

Confusion matrices help us understand how well the system is identifying each type of cacao bean. They show where the model is doing well and where it is making mistakes by comparing the actual labels with the predicted ones.

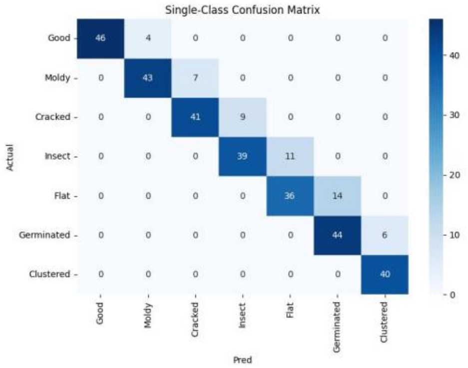

Fig. 6. Single-Class Confusion Matrix

In the single-class test, the system did a good job identifying Good, Moldy, and Germinated beans. These were correctly predicted most of the time. However, there were some mistakes in classifying Flat and Insect-infected beans. These types often look similar to other beans, making them harder to detect correctly. This shows that the model works well for clear defects but struggles with those that look almost normal.

Fig. 7. Binary-Class Confusion Matrix

In the binary-class test (Good beans vs. one defect type at a time), the system showed strong accuracy, especially with Moldy, Cracked, and Insect-infected beans. But there was some confusion between Good vs. Germinated and Good vs. Flat. Germinated beans sometimes look like Good ones, especially if the sprout is small. Flat beans can also be mistaken for Good beans because they have similar color and texture. This means the system may need more examples or clearer features to improve in these cases.

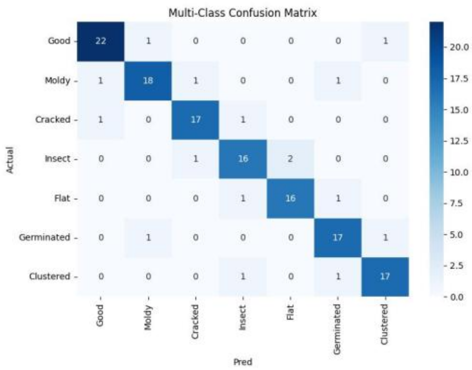

Fig. 8. Multi-Class Confusion Matrix

In the multi-class test (all classes tested at once), the system kept a good balance overall. Still, there was confusion between Cracked and Moldy beans and also between Germinated and Clustered beans. These mistakes likely happened because some beans look alike, especially when multiple beans are close together or overlapping in the image.

Even with these challenges, the model was still able to perform well. However, real-world conditions make classification harder due to lighting, camera angles, and overlapping beans.

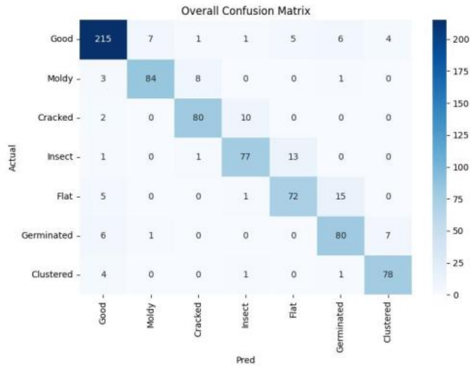

Fig. 9. Overall Confusion Matrix of Three (3) Classes

The overall confusion matrix, which combines all test results, showed that Good beans were almost always correctly classified, which is important for sorting high-quality export beans. But Flat, Germinated, and Insect-infected beans were the most commonly misclassified. This was likely because their visual features are not always easy to detect, especially if they are small or unclear.

4.11 Real-Time vs Manual Human Classification Analysis

A comparative analysis between the real-time classification system and manual human sorting revealed a consistent advantage for the automated model. The model achieved an overall accuracy of 83.51%, surpassing the 80.68% accuracy of manual classification by a margin of 2.83%.

Table 8. Real-Time vs Manual Human Classification Results.

Test Category	Real-Time Accuracy	Manual Human Classification Accuracy
Single-Class Tests	82.57	80.29
Binary-Class Tests	84.29	80.86
Multi-Class Tests	83.89	81.21
Overall Total	**83.51**	**80.68**

The real-time model outperformed manual classification in all tests. It achieved 83.51% overall accuracy, compared to 80.68% for manual sorting. The system performed better in identifying clear and subtle defects, especially in challenging cases like Good vs. Germinated. Unlike manual sorting, it was not affected by fatigue or lighting, making it more consistent. Although some errors occurred—like mislabeling Moldy as Flat—the system still made fewer mistakes than human sorters. Its speed, reliability, and objectivity make it a practical tool for improving bean quality and reducing labor in farm environments.

5. CONCLUSION

The proposed system successfully automated the classification of dried cacao beans using image-based deep learning. YOLOv8n was effective in detecting and categorizing bean defects with over 83% real-time accuracy. The system demonstrated strong potential for post-harvest automation. Future developments include deploying the model on mobile or web interfaces, refining low-performing classes, and increasing dataset diversity.

6. RECOMMENDATIONS

To improve the cacao bean defect detection system, it is recommended to combine traditional physical inspection methods, like the cut test, with automated detection. Relying solely on manual inspection risks human error and subjective judgment. Combining both methods can provide more accurate and reliable quality control in practice.

Adding more images to the training dataset, especially of different cacao bean types and defect categories, is also advised. A balanced and larger dataset helps the model better understand various defects and avoid bias, resulting in improved accuracy across diverse scenarios. For future work, exploring other versions of the YOLO algorithm, such as YOLOv5, YOLOv7, or smaller models like YOLOv8s, could reveal options for better performance or faster inference. Testing the model on different cacao bean varieties will further validate its flexibility and usefulness for the cacao industry.

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