



Seed Quality Detection Through NutriAI System in Sacha Inchi Agribusiness Development

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ABSTRACT

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YOLOv8, sacha inchi, computer vision, object detection, seed quality

This research aims to develop an automated quality detection system for sacha inchi seeds utilizing the You Only Look Once version 8 (YOLOv8) algorithm based on computer vision. The implementation of this method is expected to replace manual assessment processes that are subjective, slow, and inconsistent. The dataset used comprises 1,034 images consisting of 954 images for training, 40 images for validation, and 40 images for testing. All images underwent preprocessing, including auto-orientation, resizing to 640 × 640 pixels, and data augmentation encompassing rotation, flipping, shear, saturation and exposure adjustments, as well as cropping portions of image areas. Training was conducted using the YOLOv8s model with the default configuration for 60 epochs. Evaluation results demonstrated a precision of 0.80, recall of 0.85, and mean Average Precision (mAP@0.5) above 0.85, as well as mAP@0.5:0.95 of approximately 0.50. Based on the confusion matrix, the model successfully classified the 'Good' and 'Broken' classes effectively, although minor errors remained in the 'Poor' class. These results indicate that YOLOv8 holds substantial potential for computer vision-based automated sorting systems for sacha inchi seeds. These findings demonstrate not only the substantial potential of YOLOv8 for implementation in automated sorting systems but also offer a measurable solution for quality assessment in sacha inchi seed processing within the commercialization of sacha inchi products and broader agricultural product applications.

1. INTRODUCTION

The sacha inchi plant (*Plukenetia volubilis* L.) represents a crop with significant economic development potential as a high-nutrition food source [1-4]. Sacha inchi, as a nutrient-rich plant, contains substantial oil content (48-50%) and healthy protein (27-28%) [5-8]. Oil derived from sacha inchi seeds possesses valuable compounds in large quantities [9] and is rich in unsaturated fatty acids [10-14]. The sacha inchi plant contains essential fatty acids, particularly omega-3 and omega-6, which are excellent for dietary supplements [12, 15]. In Peru, sacha inchi oil (1 to 4%) is added to meet public health and safety requirements [16].

Seed quality serves as a critical factor in determining market value and oil extraction efficiency, particularly for sacha inchi seeds. However, seed quality classification processes are generally still conducted manually through human visual inspection, which is inherently prone to subjectivity. The limitations of manual inspection become especially apparent in large-scale processing facilities, where maintaining consistent quality standards for thousands of seeds presents a formidable challenge. Recent advances in computer vision and deep learning offer promising solutions to address these challenges [17, 18]. Among various object detection algorithms, the You Only Look Once (YOLO) family has distinguished itself through its remarkable balance between

speed and accuracy—attributes highly valuable for real-time industrial applications [19]. YOLOv8, the latest iteration in this family, introduces several architectural innovations including anchor-free detection mechanisms, decoupled head design, and enhanced computational efficiency, making it exceptionally well-suited for agricultural sorting applications [20, 21].

Precision intelligent monitoring systems hold potential for enhancing efficiency in providing information about harvest quality and quantity, which can be applied to sacha inchi seeds [22]. Industry 4.0 brings transformative changes to agricultural business by integrating IoT and Artificial Intelligence technologies [23], while smart agriculture can produce more effective outcomes through data-driven precise decision-making [24]. This aligns with the principle that digital agriculture can leverage modern information technology in production [25]. For instance, sensors through digital imaging and deep learning can visualize fruit image segmentation at different maturity levels [26], thereby reducing information asymmetry through digital technology [27].

The integration of computer vision, IoT, and artificial intelligence also has relevance for sustainable agricultural development because more consistent post-harvest sorting can reduce human error, limit product loss, and support value-chain standardization. In the case of sacha inchi agribusiness, seed quality directly affects product quality, oil extraction

efficiency, and downstream commercialization. For that reason, this study focused on a practical baseline problem: developing and evaluating a YOLOv8-based detection system for sachá inchi seed quality assessment. The expected contribution is not only technical classification performance, but also an initial digital tool that may support more efficient and more consistent post-harvest handling in future agribusiness workflows.

From a computer vision perspective, this study addresses a detection problem rather than a simple image-classification task. A single image may contain one seed or multiple seeds, and the system must localize each object and assign a quality label at the same time. This is why YOLOv8s is relevant in this context: the model supports end-to-end feature extraction, bounding-box regression, and class prediction within one pipeline. In practical terms, the computer vision contribution of this work lies in converting manual visual inspection into a computational workflow consisting of image acquisition, annotation design, preprocessing, augmentation, object detection, and confidence-based decision output. Such a workflow is important for informatics because it transforms a subjective post-harvest judgment process into a reproducible, data-driven inspection procedure that can later be connected to smart sorting, digital traceability, and AIoT-based monitoring systems. In light of these developments, this research aims to bridge the gap between traditional manual inspection and modern automated systems by developing and evaluating a YOLOv8-based detection system specifically designed for sachá inchi seed quality assessment through automated sorting in post-harvest processes.

2. MATERIALS AND METHODS

2.1 Dataset collection and preparation

2.1.1 Image acquisition protocol

Dataset collection was conducted independently to obtain image variations more representative of actual field conditions. The image capture process was performed directly using a digital camera with natural daylight illumination to ensure clear recording of object details. Each object was

placed on a flat surface with a plain background to enhance contrast between objects and background, facilitating easier recognition by the image processing system. The distance between the camera and object was maintained constant at approximately 5 to 10 centimeters, with a perpendicular shooting angle to the background plane to produce proportional visual displays. Each image was recorded in JPEG format with high resolution, approximately 3000×4000 pixels, to preserve sharpness of texture, color, and object shape. After the capture process, all images were manually inspected to ensure proper focus, lighting, and object positioning before use in the preprocessing stage.

2.1.2 Classification categories

Seeds were manually classified into five distinct categories based on visual characteristics:

Good: Seeds exhibiting intact structure, uniform coloration, and absence of physical damage.

Good Cluster: Multiple high-quality seeds in close proximity or physical contact.

Poor: Seeds displaying minor defects such as discoloration or surface irregularities.

Poor Cluster: Aggregations of seeds with significant quality deficiencies.

Broken: Seeds showing structural damage, cracks, or incomplete form.

For model training, these five descriptive groups were consolidated into three final detection labels: good, poor, and broken. Good Cluster images were relabeled as good, and Poor Cluster images were relabeled as poor. Thus, the final detector learned quality status rather than image composition. The poor class was defined narrowly as seeds with visible but non-catastrophic defects, whereas broken was reserved for seeds with clear fracture or loss of shape. This distinction is important because the poor class showed the greatest visual overlap with good seeds during evaluation.

Figure 1 presents representative single-seed images assigned to the good class. These samples show intact seed structure, relatively uniform color, and no visible cracks or major surface defects, which form the visual basis of the good label during annotation.

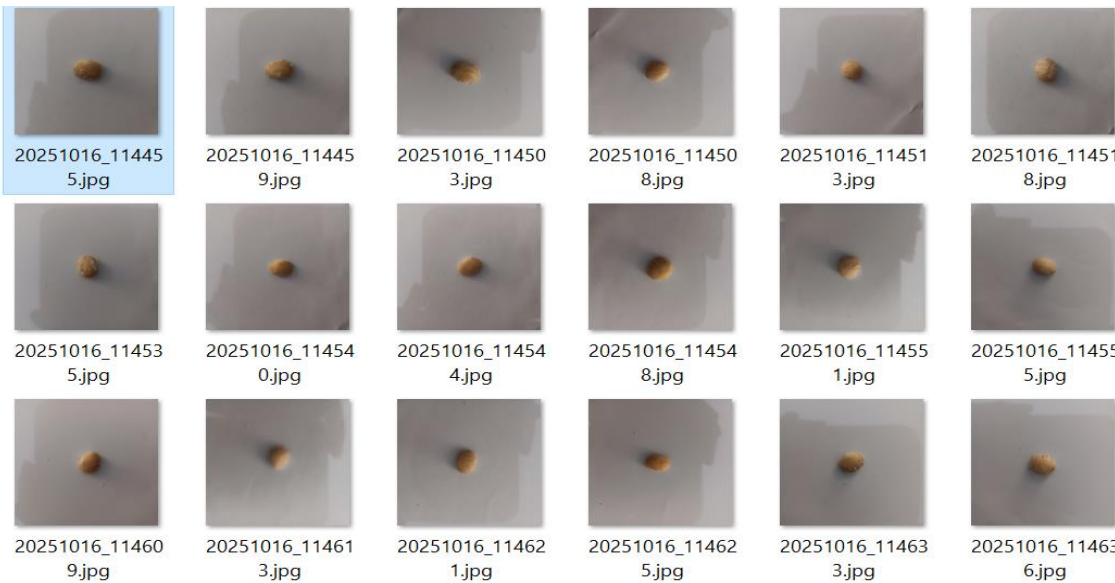


Figure 1. Good sachá inchi dataset

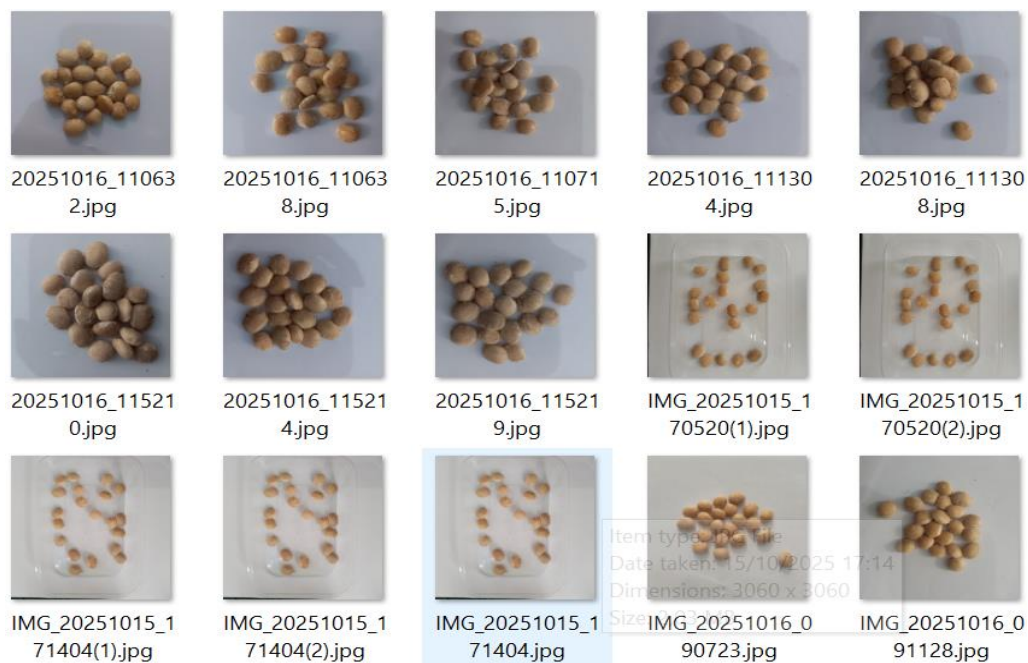


Figure 2. Good cluster sachu inchi dataset

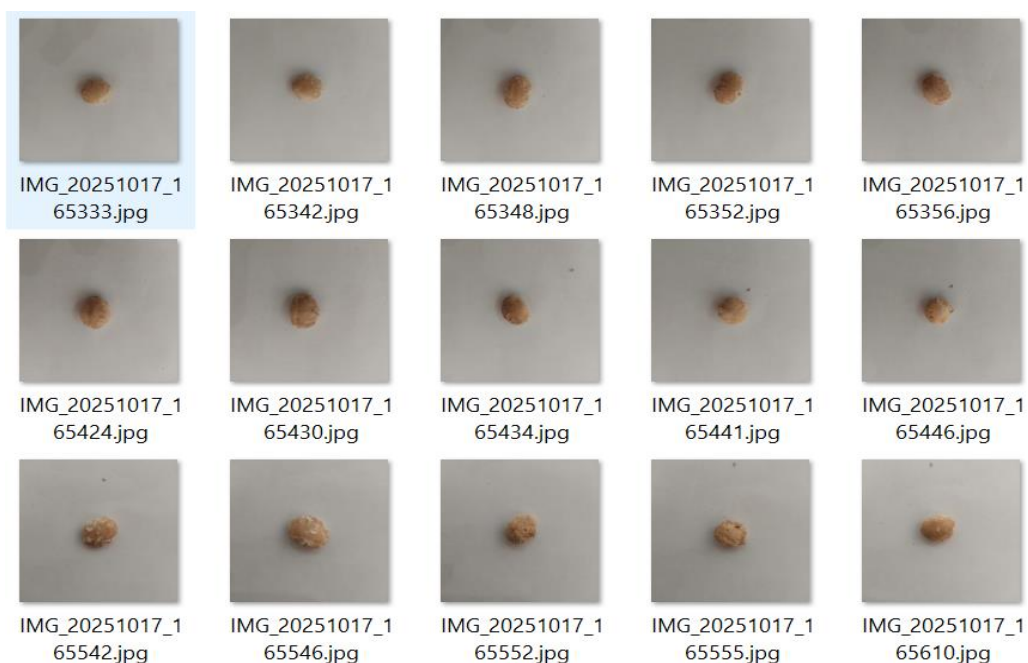


Figure 3. Poor sachu inchi dataset

Figure 2 shows representative cluster images of good-quality seeds. These images were collected to capture detection conditions in which several intact seeds appear close together or overlap, so the model can learn good-class features under denser object arrangements.

Figure 3 displays representative single-seed images assigned to the poor class. The seeds in this group retain most of their body shape but exhibit minor visual defects, such as uneven color, slight deformation, or surface irregularity, which make this class more difficult to separate from the good class.

Figure 4 presents clustered poor-quality seeds. This figure is important because it combines minor-defect appearance with multi-object scenes, creating a more challenging condition in which the model must distinguish poor seeds

when they are adjacent, partially overlapping, or arranged irregularly.

Figure 5 shows representative samples of the broken class. These seeds exhibit clear structural damage, including cracks, missing parts, and fragmented form, which makes the broken class visually more distinct than the poor class.

The initial field data collection produced 1,077 image files. After removing blurred, duplicated, poorly exposed, and otherwise unsuitable images, 400 high-quality images were retained, uploaded to the Roboflow platform, and annotated for model development. Following augmentation, the working dataset consisted of 1,034 images acquired under several lighting conditions and viewing angles. Each visible seed instance was annotated with an individual bounding box whenever its boundaries could still be visually separated.

Cluster images were therefore labeled at the seed level rather than with a single box around the full cluster. Images in which seed boundaries were too ambiguous were excluded during manual filtering. Representative labeled outputs are shown in Section 3.

The working dataset was split into 954 training images, 40 validation images, and 40 test images. All annotations used the three final labels: good, poor, and broken in YOLO format. Preprocessing included auto-orientation and resizing to 640×640 pixels. Augmentation included horizontal and vertical flipping, 90° rotation, random rotation between -15° and $+15^\circ$, shear of $\pm 10\%$, and saturation and exposure adjustments of $\pm 15\%$ and $\pm 10\%$, respectively. Because the augmented dataset was organized within the platform workflow used in this

study, possible similarity between augmented samples across splits cannot be fully excluded. This issue should be treated as a methodological limitation, and future work should split the original images first and apply augmentation only to the training subset.

2.2 Data preprocessing

The preprocessing stage standardized image orientation and input size before training. Each image underwent auto-orientation to correct image direction, followed by resizing to 640×640 pixels to match the YOLOv8 input requirement. This step improved consistency during feature extraction and reduced unnecessary variability unrelated to seed quality.



Figure 4. Poor cluster sacha inchi dataset

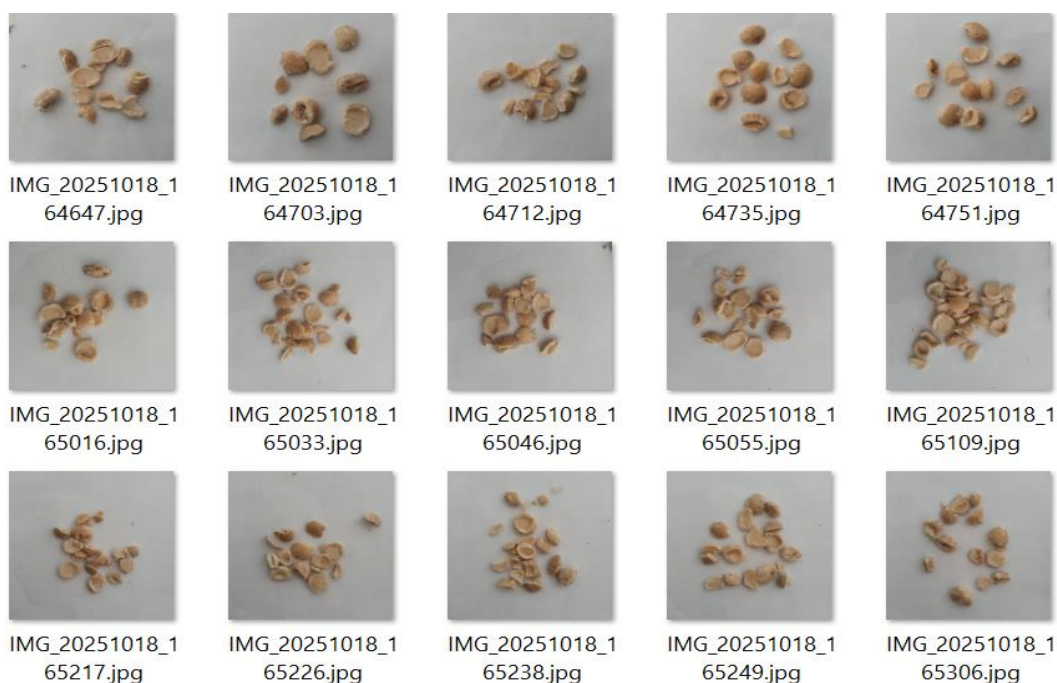


Figure 5. Broken sacha inchi dataset

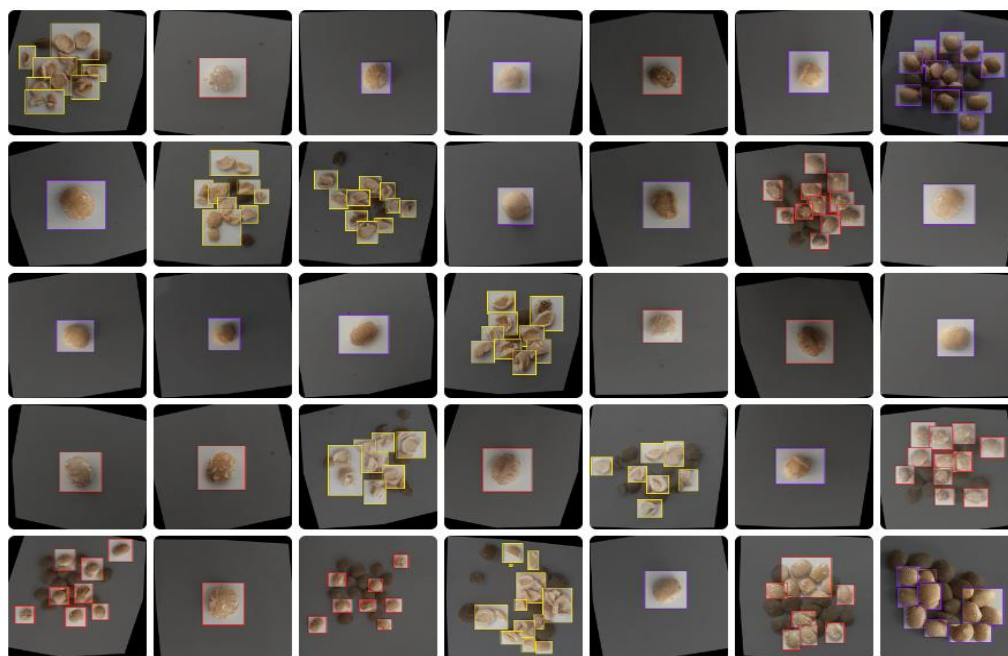


Figure 6. Data augmentation results

2.3 Data augmentation

Data augmentation was applied to increase image diversity and reduce overfitting risk. The augmentation pipeline included horizontal and vertical flipping, clockwise and counterclockwise 90° rotation, random rotation between -15° and $+15^\circ$, horizontal and vertical shear of $\pm 10\%$, and saturation and exposure adjustments of $\pm 15\%$ and $\pm 10\%$, respectively. These transformations were intended to improve robustness to moderate changes in viewing angle and illumination, although they did not simulate all conditions of a real conveyor-based sorting environment.

Figure 6 illustrates examples of augmented images generated from the original dataset. The transformed outputs reflect changes in orientation, spatial arrangement, and lighting-related appearance, which were introduced to improve model robustness against image variation during training.

2.4 Dataset partitioning

The final working dataset contained 1,034 images divided into 954 training images (92%), 40 validation images (4%), and 40 test images (4%). This split was adequate for an initial baseline experiment, but the validation and test subsets remain small for a multi-class object-detection study. Therefore, the reported metrics should be interpreted cautiously and should be strengthened in future work by using a larger independent test set and by reporting the number of annotated seed objects per class in each subset.

2.5 YOLOv8 model architecture and training configuration

The YOLOv8s model uses an anchor-free architecture with three main components: backbone, neck, and head. The backbone applies CSPDarknet-based feature extraction, the neck uses a Path Aggregation Network (PAN), and the head separates classification and bounding-box regression through a decoupled design. Training was conducted for 60 epochs in

Google Colab on an NVIDIA T4 GPU with batch size 16 and the AdamW optimizer. The experiment used the standard pretrained YOLOv8s initialization available in the Ultralytics framework, while the remaining hyperparameters followed the framework defaults in the executed training configuration. Because this study did not perform systematic hyperparameter tuning or model comparison, the resulting performance should be treated as a baseline for *sacha inchi* seed detection rather than as an optimized benchmark.

3. RESULTS AND DISCUSSION

The model produced encouraging baseline performance. Overall precision reached 0.80, recall reached 0.85, $mAP@0.5$ exceeded 0.85, and $mAP@0.5:0.95$ was approximately 0.50. The training curves showed a general reduction in box loss, classification loss, and distribution focal loss across the 60-epoch training period.

Figure 7 summarizes the training dynamics of the YOLOv8s model. The training losses decrease steadily across epochs, while the validation curves fluctuate, indicating that learning progressed but evaluation stability was affected by the limited validation set size.

The model showed progressive learning during training, as reflected by the downward trend of the training losses. However, the validation losses and precision-recall curves also showed noticeable fluctuations. Given the small validation subset, these fluctuations should be interpreted carefully, and they do not allow a strong claim that overfitting was absent. Accordingly, the present results are better described as stable enough for a baseline experiment rather than fully converged for deployment.

Confusion matrix analysis indicated that the model recognized the good and broken classes more consistently than the poor class. The main source of error appeared in the boundary between good and poor seeds, where visual differences were relatively subtle. Inference outputs commonly showed confidence values above 0.80 for clearly separable seeds, but errors increased in images with more

ambiguous appearance.

Figure 8 presents the confusion matrix for the three final labels: good, poor, and broken. The stronger diagonal pattern

for good and broken indicates better class separation, whereas the off-diagonal values involving poor confirm that this class was the main source of confusion.

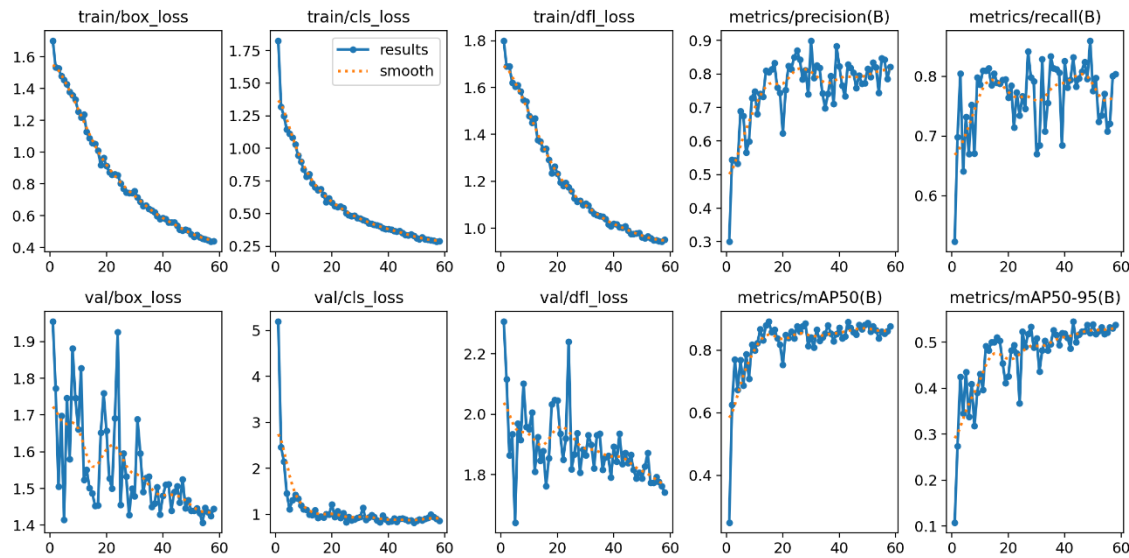


Figure 7. YOLOv8s training curves for sachai inchi seed detection

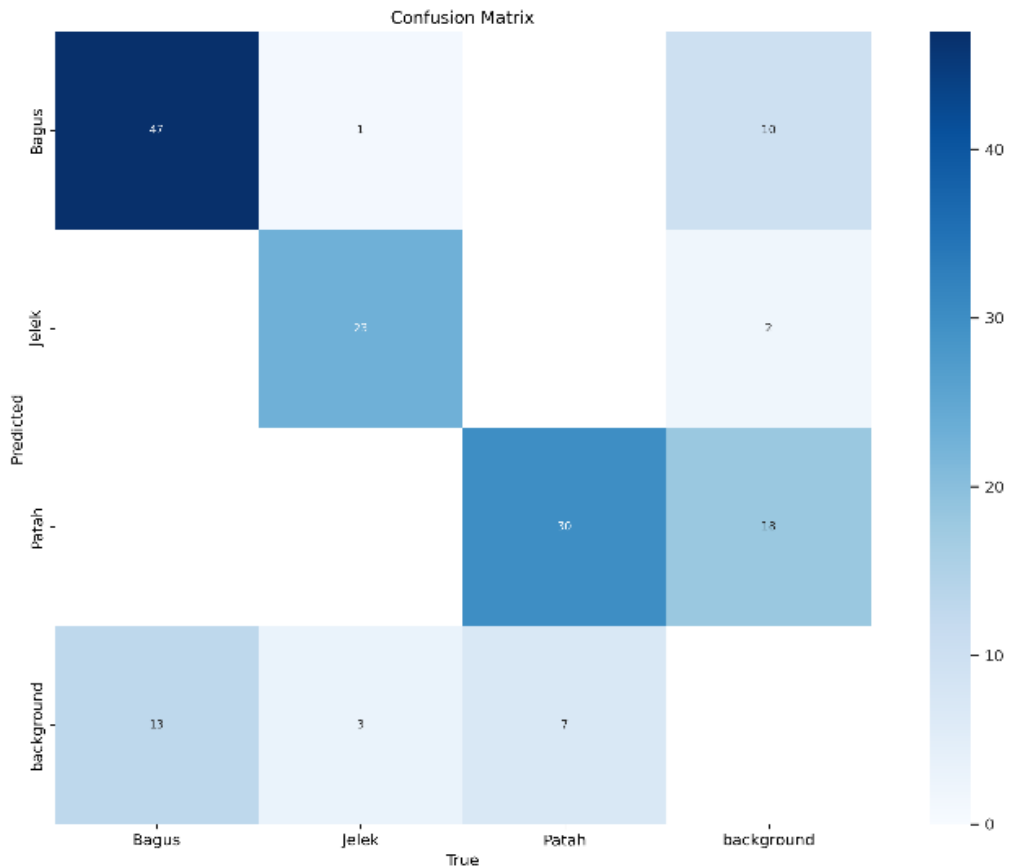


Figure 8. Confusion matrix of the final seed-quality labels

Overall, YOLOv8s demonstrated promising detection and classification capability for sachai inchi seed quality assessment. The model can therefore be considered a feasible baseline for future automated sorting research, but the current study does not yet demonstrate operational readiness on an industrial sorting line.

From an application perspective, precision of 0.80 means

that most positive detections were correct, while recall of 0.85 indicates that the model detected a large share of the target seed conditions. The mAP@0.5 value above 0.85 shows strong detection performance at a standard IoU threshold, whereas the mAP@0.5:0.95 value of about 0.50 suggests that localization accuracy still decreases under stricter overlap criteria. This pattern is reasonable for small and visually

similar agricultural objects, especially when some seeds appear close together or partially overlap.

The results can also be interpreted from a computer vision standpoint. The relatively strong $mAP@0.5$ indicates that the detector was able to capture dominant visual cues such as overall seed shape, boundary integrity, fragmentation, and gross surface appearance. However, the drop in $mAP@0.5:0.95$ and the confusion between good and poor suggest that fine-grained feature discrimination remains challenging when defects are subtle. In other words, the current model is already effective for coarse visual quality separation, especially for clearly broken seeds, but it is still less robust for borderline samples that require finer texture, color, and contour interpretation. This finding confirms that the main technical challenge is not merely object presence detection, but fine-grained agricultural object assessment under visually similar class conditions.

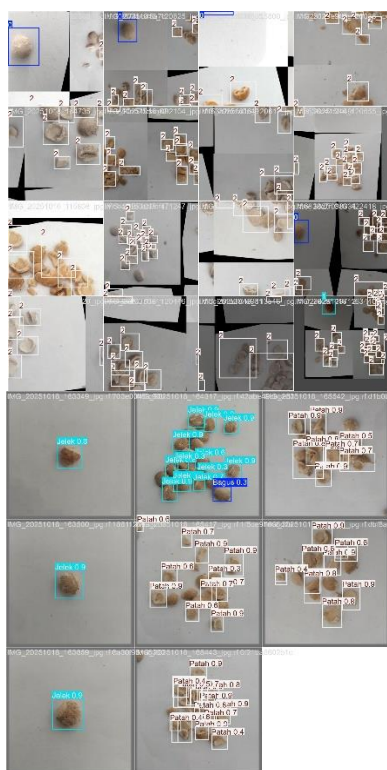


Figure 9. Representative detection outputs on validation and test images

Figure 9 shows representative detection outputs produced by the trained model on validation and test images. The predicted bounding boxes and confidence values indicate that the model was generally able to localize and classify individual seeds, although dense scenes and borderline poor samples remained more challenging.

The per-class behavior visible in the confusion matrix and detection outputs confirms that the good class achieved the strongest separation, whereas the poor class overlapped with good more often. This result is consistent with the class-definition problem itself, because poor seeds were defined by minor external defects rather than by severe structural damage. The finding suggests that future studies should refine the visual criteria of the poor class, involve more than one annotator for at least part of the dataset, and expand borderline examples during data collection.

The study also has practical relevance for sustainable

agricultural development. More consistent seed sorting may reduce avoidable mixing between high-quality and lower-quality seed lots, support more standardized post-harvest handling, and improve traceability in sachai inchi agribusiness value chains. At the same time, the present experiment has three important limitations. First, image acquisition was relatively controlled. Second, only one model configuration, YOLOv8s, was tested. Third, no external test on conveyor footage, edge devices, or real throughput was performed. Therefore, the present findings should be interpreted as evidence of application potential, not proof of industrial deployment readiness.

Future research should address these limitations by splitting original images before augmentation, expanding the independent test set, reporting class-level precision, recall, F1-score, AP, and sample size, and comparing YOLOv8s with lighter and larger alternatives such as YOLOv8n and YOLOv8m. Additional work is also needed to test the model under real sorting-line conditions, including variable backgrounds, motion blur, shadows, reflections, and throughput constraints.

4. CONCLUSIONS

This study shows that YOLOv8s can support baseline detection and classification of sachai inchi seed quality from digital images. The model achieved precision of 0.80, recall of 0.85, $mAP@0.5$ above 0.85, and $mAP@0.5:0.95$ of about 0.50 under relatively controlled image-acquisition conditions. These results indicate application potential for computer vision-assisted post-harvest sorting, especially as an initial step toward more consistent and more efficient seed quality screening. Nevertheless, the present study used a small validation and test subset, evaluated only one model configuration, and did not include conveyor-based, edge-device, or external-field testing. Therefore, the proposed system should be regarded as a promising baseline and not as a deployment-ready industrial solution. From the viewpoint of computer vision, the study shows that automated seed-quality assessment can be formulated as a fine-grained object-detection problem in which localization and class discrimination must be solved simultaneously.

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