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QUALITY ASSESSMENT OF COPRA USING DEEP LEARNING AND IMAGE PROCESSING TECHNIQUES

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Abstract – *This research investigates the application of the YOLOv11 object detection model in the classification of copra images, specifically categorizing them into three distinct grades: Grade A, Grade B, and Grade C. Through performance metrics such as precision, recall, F1 score, and confusion matrices, the study assesses the model's effectiveness in accurately identifying and classifying copra grades. The findings reveal that the model achieves an overall accuracy rate of 93.65% on the testing dataset, demonstrating its proficiency in copra grade classification tasks. Furthermore, the model's performance is validated through a Cohen's kappa value of 0.90, indicating a high level of agreement with human expert labels and reflecting the model's robustness and reliability. These results hold significant implications for the agricultural sector, offering insights into the potential integration of advanced deep learning techniques for enhancing quality assessment and optimizing copra production processes.*

Keywords: copra quality, deep learning, image processing, YOLOv11.

I. INTRODUCTION

Coconuts hold a vital position in the global agricultural and industrial sectors, with many countries being major producers and cultivators. Coconut cultivation spans millions of hectares of land worldwide, providing livelihoods to millions of farmers and creating employment opportunities in various coconut-based enterprises [1]. One of the significant traditional coconut products is copra. Copra, derived from the dried kernel of a coconut, serves as a primary source for coconut oil production, with copra meal generated as a valuable by-product [2].

Making copra includes many steps, including harvesting coconuts, opening the shells, and removing the meat or white kernel. The kernels are then dried using either of these methods: kiln drying, mechanical dryers, or sun drying until they reach a moisture content of about 6–7% [2, 3]. After drying, the kernels are graded and sorted based on their quality before being sold to buyers for further processing into coconut-based products [2].

Both producers and buyers of copra find copra quality grading to be necessary. For producers, it serves as a standard means of assessing their yield quality, enabling them to negotiate better prices with buyers. Additionally, quality grading can provide valuable feedback to farmers on areas of improvement that can help them produce better quality copra. For buyers, copra quality grading ensures they receive a product that meets their needs. Grading enables them to select the copra that aligns with their requirements, and they can also use the grading information to decide on the price they are willing to pay for the copra [3].

The grading of copra also plays an indispensable role in producing coconut oil, which is one of the primary end products of copra processing. The quality of the copra directly impacts the quality of the oil produced, and hence, the grading process ensures that the produced oil meets the required standards [4, 5]. However, the current practice for grading copra usually involves a manual process, wherein copra samples are manually graded and sorted based on their physical attributes, including size, color, and

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moisture content. Trained graders visually inspect the copra samples and assign them to specific grades or categories based on their quality and market value. This conventional way of copra grading can be a time-consuming and error-prone procedure, particularly when evaluating large volumes of copra samples [6]. To mitigate these concerns, the development of deep learning-based copra grading systems is being studied as it can provide a more accurate, objective, and consistent grading process.

Traditional kiln drying has been widely used to dry various products in different regions. This approach involves the use of specialized kilns, which are enclosed structures designed to facilitate controlled drying conditions. The process typically begins by stacking the raw material inside the kiln, whether agricultural produce, timber, or other substances [7]. One of the key advantages of traditional kiln drying is its adaptability to local conditions. The construction materials and methods can vary based on regional resources and climate. For instance, kilns may be constructed using locally available timber in areas with abundant wood resources, making this method an accessible and practical drying system [8]. In arid regions, where sunlight is plentiful, kilns may incorporate passive solar heating elements to harness the sun's energy for drying [9].

The deep learning-based copra grading system employs sophisticated algorithms and models to examine copra samples and offer impartial and dependable grading outcomes. By training the system on copra sample datasets, it can acquire knowledge about the properties of high-quality copra and distinguish them from low-quality ones. This approach can significantly reduce the time and labor required for copra grading while enhancing the accuracy and consistency of the grading results. With the adoption of this technology, coconut farmers and processors can optimize their production processes, guarantee product quality, and increase their profitability.

II. LITERATURE REVIEW

Ensuring the quality of copra is essential for meeting the demands of both local and international markets while addressing consumer safety and production efficiency. Recent advancements in artificial intelligence (AI), visual computing, and machine learning (ML) have significantly enhanced the accuracy, reliability, and efficiency of copra quality assessment. Various studies have proposed innovative methods to automate the copra grading process, each contributing unique insights and technologies to this critical area.

For instance, Poojitha et al. [10] developed an AI-powered automated system to evaluate copra quality based on size, color, shape, and sulfur content. This system addresses the need for consistent and efficient grading practices, reducing labor costs and minimizing human error. Building on improving accuracy and reliability, Lakshmanan et al. [11] proposed a complementary approach using support vector machine (SVM) classification to tackle issues like moisture, mold, and sulfur content. Their method, which segments copra images using the SUSAN filter, demonstrated an impressive 90.4% accuracy, emphasizing the utility of machine learning in distinguishing high-quality copra from substandard products.

Expanding on using AI for classification, Sagayaraj et al. [12] explored machine learning's potential in predicting sulfur content – a significant health concern. By employing a feed-forward ML technique, their study promoted safer production practices and achieved a validation accuracy of 96.5%, reinforcing the effectiveness of AI-driven solutions in ensuring consumer safety. Another study by Mohan et al. [13] introduced a hardware-integrated solution. Their innovative system, combining ESP-32 camera modules and conveyor belt mechanisms, automates detecting and removing defective copra, further enhancing productivity and profitability. This shift from pure software-based approaches to integrated systems highlights the diverse applications of technology in addressing industry needs.

Galindo et al. [14] also investigated meat dryness, a crucial parameter in copra grading, utilizing the faster region-based convolutional neural network (Faster R-CNN) with an Inception v2 architecture. Their study achieved an overall accuracy of 87.67%, effectively categorizing copra into dryness levels. This work complements prior studies by focusing on a specific grading criterion, further advancing the standardization of copra quality assessments.

Finally, the closest literature to this study is the work by Colubio et al. [2], who introduced a convolutional neural network (CNN)-based framework to grade copra according to the Philippine National Standard (PNS). Their system, which achieved 90.74% accuracy, exemplifies how CNNs can reliably classify copra into standardized grades, thus supporting producers in maintaining market compliance.

Table 1 provides an overview of the studies on copra quality assessment and classification. It outlines the algorithms used, the criteria for classification, and the accuracy achieved in each study. This comparison helps illustrate the methodologies employed across various research efforts and their respective performance outcomes.

III. RESEARCH METHODS

A. *Conceptual framework design*

Figure 1 illustrates the architectural design for this study, which processes copra images and classifies them based on quality categories. The workflow is structured around the YOLOv11 model, an advanced real-time object detection and classification algorithm. YOLOv11 enhances its predecessors, significantly improving speed, accuracy, and feature extraction. It builds upon this legacy with further enhancements in feature extraction, efficiency, and multi-task capabilities [15].

The YOLOv11 architecture comprises three main components: the backbone, neck, and head. The backbone plays a key role in extracting essential features from the input copra images across different scales. This component consists of multiple convolutional (Conv) blocks, each containing three subblocks: Conv2D, BatchNorm2D, and the SiLU activation function, ensuring comprehensive feature extraction and improved detection performance [15–17].

The neck component bridges the backbone and head. It aggregates features from multiple scales and transmits them to the head for predictions. The head is the final component of the YOLOv11 model and plays a crucial role in generating predictions. It determines the object class, calculates the objectness score, and predicts bounding box dimensions for identified objects. Unlike earlier YOLO versions, YOLOv11 uses an anchor-free approach for bounding box prediction, simplifying training, and improving detection accuracy, especially for non-uniform objects like copra [15–17].

The YOLOv11 model employs advanced activation functions for optimized predictions throughout the process. The Sigmoid activation function calculates objectness scores, while the SoftMax activation function assigns probability scores for classification tasks. These mechanisms ensure precise categorization of copra into predefined quality grades and improve model performance [17].

B. *Dataset preparation*

Researchers collected copra images from a local company in Southern Leyte Province to create the dataset for copra quality assessment. The company's copra quality experts carefully classified the copra into grades (Class A, B, and C) based on industry standards. The experts provided representative samples for each grade to the researchers, who then meticulously photographed them. These images were then labeled with their corresponding grade by the experts. Class A copra, with the darkest color, represents the highest grade. This collaborative approach, with experts providing classified samples and researchers capturing high-quality images, ensures a nuanced understanding of the variations in copra quality within the dataset. Sample images for each class (A, B, and C) are shown in Figure 3.

Table 2 presents the distribution of samples across different classes within a copra image dataset. It comprises four columns: 'Class' which specifies the copra grade; 'Training' indicating

Table 1: Summary of related studies

Study	Algorithm/Method Used	Classification Criteria	Accuracy
Poojitha et al. [10]	Artificial intelligence (AI) and image processing.	Size, color, shape, sulfur content.	Not specified
Lakshmanan et al. [11]	Support vector machine (SVM)	Moisture, mold, wrinkles, sulfur content (usable vs. unusable)	90.4%
Sagayaraj et al. [12]	Feed-forward machine learning	Sulfur content prediction	96.5%
Mohan et al. [13]	Integrated hardware solution (ESP-32, IR Sensor, etc.)	Defective vs. non-defective copra	Not specified
Galindo et al. [14]	Faster region-based CNN with Inception v2	Dryness levels (Optimally Dry, Under-Dry, Over-Dried)	87.67%
Colubio et al. [2]	Convolutional neural network (CNN)	Philippine National Standard (Grade I, II, III)	90.74%

Fig. 1: Conceptual framework of the study

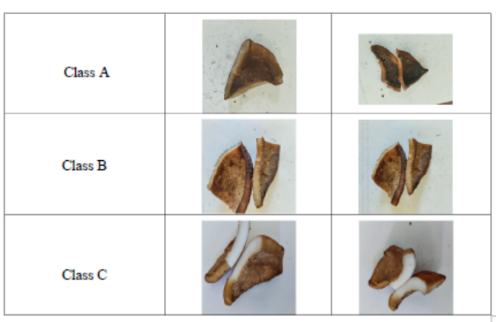

Fig. 2: Metadata of image samples

the number of images used for training a machine learning model; ‘Validation’ representing the number of images used for model validation; and ‘Testing’ denoting the number of images used for testing the model. In total, the dataset includes 1,254 images.

C. Implementation

The study utilized various technology tools to support machine learning and image processing tasks. Python version 3.10.12, accessed through the Anaconda distribution, served as the primary programming language. TensorFlow was used as

Table 2: Dataset for this study

Class	Number of Images			Total (Class)
	Training	Validation	Testing	
Class A	296	91	36	423
Class B	300	85	40	425
Class C	282	74	50	406
Total (Subset)	878	250	126	**1,254**

the backend for running Keras, while NumPy provided essential mathematical functions for computing multi-dimensional arrays and matrices, which were crucial for image analysis. Google Colab facilitated writing and executing Python code in a cloud-based environment for model training and testing. Additionally, PyTorch was employed for its flexible and dynamic computational graph capabilities, allowing adaptive deep learning model development.

For copra quality assessment, YOLO (You Only Look Once) was integrated as the object detection system to identify and classify copra quality in images or video frames with a single forward pass. OpenCV played a vital role in image and video processing, providing tools for image enhancement, segmentation, and feature extraction. The RoboFlow API was utilized for image annotation, dataset preparation, model training, and deployment, ensuring high-quality labeled data for deep learning models. Lastly, Comet ML was employed for experiment tracking, model visualization, and performance optimization, allowing systematic evaluation and refinement of deep learning algorithms. These tools collectively contributed to the efficient development and implementation of an automated copra quality assessment system.

D. Model performance evaluation

Following the model's training phase, a critical step involves evaluating its performance on unseen data using a test dataset and key performance metrics. These metrics provide valuable insights into the model's generalization capability and can pinpoint areas for further refinement. The evaluation considers several performance metrics, including accuracy (Formula (1)), precision (Formula (2)), recall (Formula (3)), F1 score (Formula (4)), and mean Average Precision (mAP) (Formula (5)).

IV. RESULTS AND DISCUSSION

Figures 3 and 4 provide insights into the training and validation process of a YOLOv11 neural network for classifying copra images by grade (A, B, or C). Figure 3 illustrates the mosaic data augmentation technique, where smaller images are combined into a single larger image, Increasing the variety of training data and enhancing the ability of the model to generalize to new, unseen data. Bounding boxes around copra objects in this composite image highlight the presence and classification of copra. Figure 4 presents validation results, showing copra images with both ground truth labels and the model's predictions, allowing an assessment of the model's accuracy and localization precision.

Figure 5 illustrates the relationship between different label dimensions, width, and height of bounding boxes in the model, depicted as a 2D histogram. Each cell represents the number of bounding boxes with specific width and height dimensions, with brighter cells indicating a higher concentration of bounding boxes of those dimensions. This visualization helps identify patterns or correlations that may be useful for understanding the distribution of object annotations in data. For instance, a diagonal line of bright cells suggests that the model tends to co-occur frequently in the same image or that certain

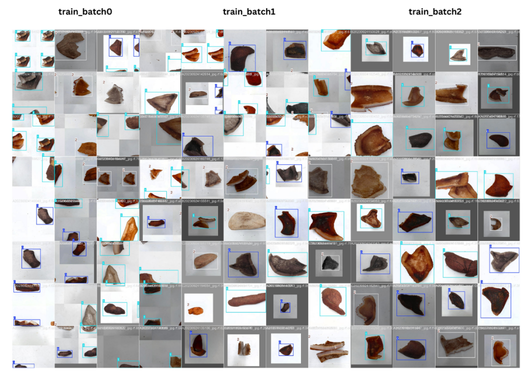

Fig. 3: Visualization of training images batch with mosaic data augmentation

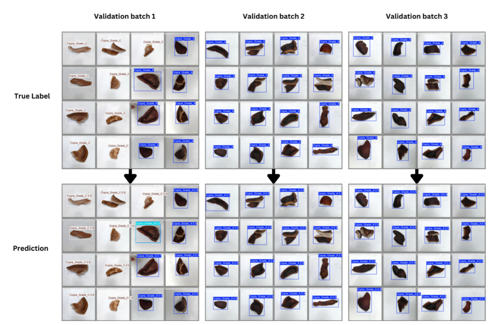

Fig. 4: Visualization of copra validation

classes are more likely to appear at specific scales. This information can be valuable for understanding the characteristics of the dataset and for informing decisions related to model training and evaluation.

The distribution in this figure is symmetric and likely resembles a normal distribution, with a cluster of bright cells around (0.5, 0.5) and another around (0.25, 0.5). This indicates that the model tends to predict boxes with equal dimensions and those twice as tall as wide. The smooth distribution with few scattered bright cells suggests the YOLOv11 model generates bounding boxes with consistent and accurate dimensions for the copra objects. Accurate bounding box predictions are crucial for performance, as they ensure the model can correctly identify and localize copra objects, enhancing the accuracy of the grade classification.

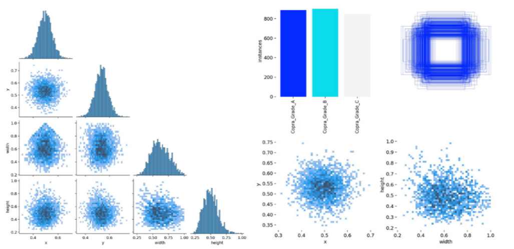

Fig. 5: Visualization of correlogram labels

YOLOv11 object detection model was employed to detect and classify copra images into three quality grades: Grade A (highest), Grade B, and Grade C (lowest). During training, the model demonstrated high performance in detecting and classifying copra objects, as measured by mean Average Precision (mAP). Additionally, precision, recall, and F1 scores were utilized to provide a more comprehensive evaluation of the model's effectiveness. A confusion matrix for the training data was also generated to visualize the model's performance across all classes.

Figure 6 showcases the model's performance during the training phase, displaying the mean AP_0.5, which measures the model's accuracy at an IoU threshold of 0.5 across training epochs. The plot indicates a consistent increase in accuracy, with the model achieving a peak mAP of 98.52% at 100 epochs. This high mAP suggests that, on average, the model correctly detected and classified the copra grade in 98.52% of the training images. While this suggests high overall accuracy, it also acknowledges the possibility of some misclassifications, which can be further explored using the confusion matrix.

Figure 7 illustrates the trend of precision and recall across 100 epochs on training and validation sets. In object detection, precision and recall are performance metrics that evaluate the accuracy of a model's predictions. They are determined by the number of true positives (TP), false positives (FP), and false negatives (FN) produced by the model [18].

The graph shows a significant improvement in

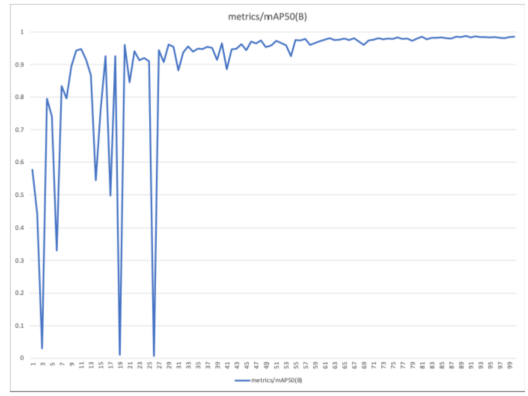

Fig. 6: Training AP_0.5 plot of the YOLOv11 model

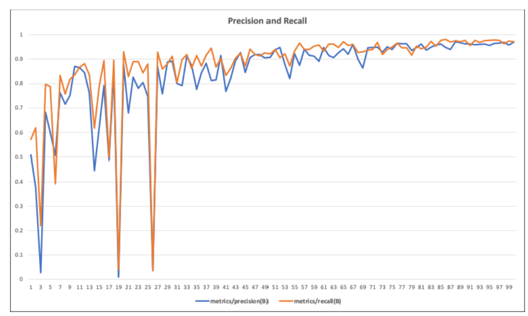

Fig. 7: Precision and recall plot of the YOLOv11 model

the model's ability to discern between relevant and irrelevant instances. Recall consistently surpasses precision and has achieved a precision of 0.97045 and a recall of 0.97222 at epoch 100. This suggests the model prioritizes identifying as many relevant instances as possible, even at the cost of an increased number of false positives. While this approach minimizes missed relevant instances, it may reduce the overall reliability of positive predictions.

Figure 8 provides insights into how the model's performance evolved during training. The evaluation used the loss function, which quantifies the discrepancy between the model's predicted copra grades and the actual labels for both the training and validation sets. Lower loss values indicate better agreement between predictions and actual labels. Throughout the training period, the model achieved notable milestones in minimizing loss. At epoch 100, box loss reached its minimum value of 0.5807, indicating precise bounding box localization. Classification loss (Cls Loss) achieved a minimum of 0.25534, suggesting an accurate classification of copra grades, and distribution focal loss (Dfl Loss) reached its minimum of 1.111, indicating the model's confidence in detecting copra objects within the images. These results reflect the model's progressive improvement and ability to learn and adapt to the copra image classification task effectively.

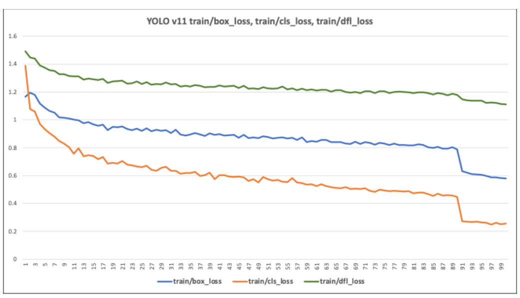

Fig. 8: Training bounding box, classification, and object loss

In Figure 9, the validation loss values – box_loss of 0.80165, cls_loss of 0.32853, and dfl_loss of 1.22417 at 100 epoch – demonstrate that the model performs well on the validation datasets and can accurately classify the grade of copra. These findings confirm the efficacy of the YOLOv11 deep learning approach in precisely categorizing copra grades.

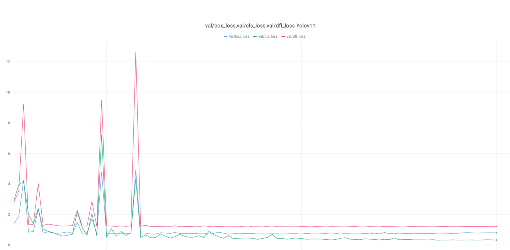

Fig. 9: Validation bounding box, classification, and object loss

Furthermore, the model's performance during training is evaluated using a confusion matrix visualized in Figure 10. This matrix shows how well the model's predicted copra grades (A, B, C) match the actual grades. Each cell in the matrix represents the number of images for a specific combination of predicted and actual grades. Values along the diagonal indicate correct classifications (true positives - TP), where the model accurately identified the copra grade. Darker colors in these cells suggest more frequent correct predictions. Lighter colored off-diagonal cells represent misclassifications, including false positives (FP), where the model predicted the wrong grade, and false negatives (FN), where the model missed copra objects or assigned an incorrect grade. The dominance of darker colors along the diagonal suggests the model performs well in distinguishing copra grades during training.

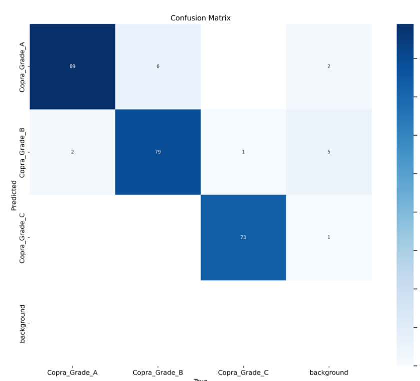

Fig. 10: Training phase confusion matrix

On the other hand, the normalized confusion matrix (Figure 11) highlights the model's performance relative to the total number of samples in each class. The model correctly classified 98%, 93%, and 99% of the true Grade A, Grade B, and Grade C samples, respectively. This indicates strong performance in distinguishing between the three classes. However, the presence of false positives and false negatives suggests that there is still room for improvement in the model's accuracy and reliability.

Figure 12 focuses on evaluating the model's performance in practical applications. It show-

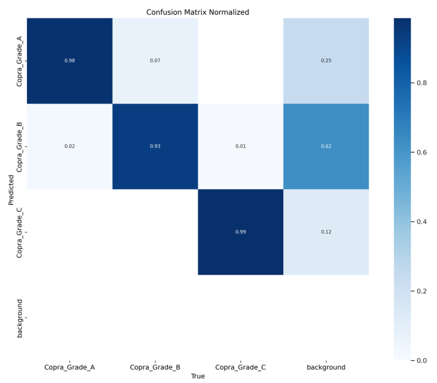

Fig. 11: Training phase normalized confusion matrix

cases a comparison between ground-truth copra images and the predictions generated by the YOLOv11 model applied to the validation and testing copra dataset to evaluate the model's effectiveness in object detection. In most cases, the model demonstrates a high degree of accuracy, correctly identifying and classifying copra grades within the images. While uncommon, there are a few instances where the model misclassified objects, assigning them to incorrect grades.

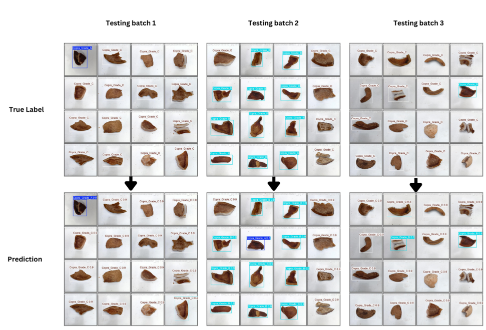

Fig. 12: Visualization of copra testing process and validation

Figure 13 dives deeper into the model's proficiency in copra grade detection and classification. It presents the F1 score, a comprehensive metric considering precision and recall, for all copra grades across various confidence thresholds. The overall F1 score of 0.97 across all grades indicates exceptional performance. These scores highlight the model's ability to detect copra objects accurately and distinguish between their grades effectively. Furthermore, the variation in optimal confidence thresholds across grades suggests the model can adapt its detection strategy for each grade, potentially due to subtle visual differences between the grades.

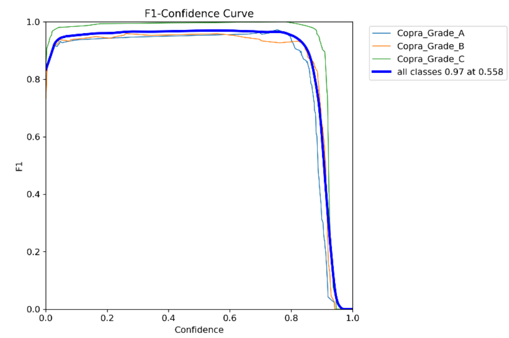

Fig. 13: F1-confidence curve of all classes

Furthermore, Figures 14 and 15 offer further insights into the model's precision and recall for copra grade classification. Figure 14 illustrates precision-confidence curves for the different copra classes. It is evident that as the confidence threshold increases, the model's precision improves across all classes. This indicates that the model is more selective in its predictions, leading to higher precision. Remarkably, the precision for all classes reaches 1.0 at a confidence threshold of 0.904, indicating that all detections made at or above this threshold are true positives. This consistency in precision, even with stricter criteria, highlights the robustness and reliability of the YOLOv11 model in accurately classifying copra grades.

Figure 15 complements these findings by presenting a precision-recall curve for the three copra grades alongside the average precision-recall score (mAP@0.5). The curve plots precision against recall as the confidence threshold is varied. Lowering the threshold increases the number of detections but may also lead to more false positives. Conversely, raising the threshold reduces detections but improves precision. The precision-recall curve demonstrates that the

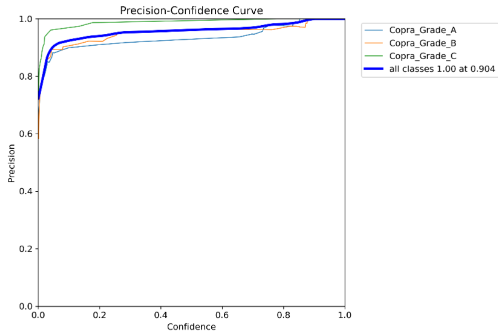

Fig. 14: Precision-confidence curve of all classes

model achieves high precision and recall for all three classes, with an average precision-recall score of 0.988, indicating exceptional overall performance. While copra-grades-C exhibits the highest precision-recall curve, all classes achieve good performance. The slight drop-off in the precision-recall curve for copra-grades-C at high recall values suggests potential challenges in detecting all instances of this class with very high confidence. However, the overall high mAP score underscores the model's ability to balance precision and recall across all copra grades.

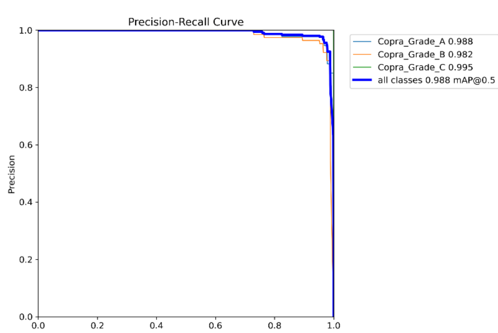

Fig. 15: Precision-recall curve of all classes

To gain a deeper understanding of how the model performs on unseen data, Figure 16 presents a confusion matrix. This visualization reveals the distribution of correct (diagonal) and incorrect (off-diagonal) predictions for each class, enabling us to identify areas for potential improvement.

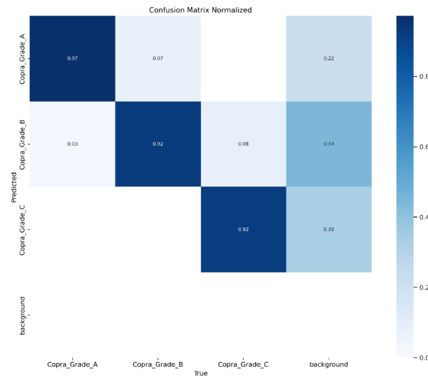

Fig. 16: Confusion matrix for the classification of copra quality using the test dataset

Remarkably, the model correctly identified 35 out of 36 instances for Grade A, achieving a 97% accuracy rate. However, it missed 1 instance, resulting in a 3% error rate. Grade B had 37 out of 40 or 92% instances correctly identified, resulting in a 7% error rate due to three misclassifications. Grade C had 46 out of 50 or 92% instances correctly identified, resulting in an 8% error rate due to four misclassifications. Overall, the model achieved an accuracy rate of 93.65% concerning the testing data. These insights offer valuable information on the model's performance across different copra grades and highlight areas for potential improvement.

Cohen's kappa statistic was employed to better understand the model's agreement with human experts. It is a statistical metric that measures agreement between the model's predictions and the actual copra grades (ground truth). The model achieved a Cohen's kappa value of 0.90. Utilizing the reference values provided in Table 3, a kappa of 0.90 suggests the model's classifications almost perfectly agree with the human expert labels. This result underscores the model's strong reliability in copra grade classification, affirming its ability to correctly identify and localize objects within an image.

The findings of this study demonstrate a significant improvement in accuracy compared to the

Table 3: Cohen's Kappa Interpretation

Kappa Statistic	Strength of Agreement
< 0	Poor
0.01–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Nearly Perfect

Source: Kim et al. [19]

closest comparable literature [2], as highlighted in Table 1. The proposed YOLOv11 model exhibited superior performance in the classification and grading of copra quality, achieving higher accuracy metrics across multiple evaluation parameters. This improvement can be attributed to the incorporation of advanced architectural features in the recent version of YOLO, which enhances feature extraction by capturing both local and global patterns in copra images.

V. CONCLUSION AND RECOMMENDATIONS

This research investigates the application of the YOLOv11 object detection model in classifying copra images into three distinct grades: Grade A, Grade B, and Grade C. The model has proven highly effective, achieving an overall accuracy rate of 93.65% and demonstrating strong agreement with human experts, as indicated by a Cohen's kappa value of 0.90. Additionally, the model's overall F1 score of 0.97, precision of 0.97045, and recall of 0.97222 highlight its effectiveness in detecting and distinguishing copra objects and their grades within unseen test images. These findings highlight the potential of deep learning techniques to advance agricultural practices, particularly in quality assessment and production optimization within the copra industry. Further research and development efforts should enhance the model's performance through continued refinement and optimization, ultimately facilitating more accurate and efficient copra grade classification processes. Additionally, exploring the integration of machine learning models, such as YOLOv11, into industrial equipment could significantly improve agricultural quality assessment.

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