Grainalyze: A Hybrid Approach for Consumer Level Assessment of Rice Quality Based on Grain Morphology

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ABSTRACT

Rice is a staple food in the Philippines, and its quality significantly affects consumer preference, market value, and grain grading standards across different regions and local agricultural markets today. However, conventional rice quality assessment commonly relies on manual inspection by trained personnel, making the process time-consuming, subjective, and often inaccessible to ordinary consumers.

This study proposes Grainalyze, a mobile-based artificial intelligence-assisted system for rice grain quality assessment using instance segmentation and image-based analysis. Image-based rice quality assessment using computer vision and machine learning techniques has been widely explored in previous studies [1], [7]. A total of 3,885 source images of rice grains were prepared and expanded to 10,135 images through preprocessing and augmentation, then annotated into four grain quality classes: whole grain, broken grain, chalky grain, and discolored grain.

The study evaluated Mask R-CNN alongside YOLOv8n-seg, YOLOv8s-seg, and U-Net using standard performance metrics, including Precision, Recall, F1 Score, mean Average Precision, and inference speed. Deep learning-based segmentation approaches have demonstrated strong performance in rice grain classification tasks [11], [19]. Results show that Mask R-CNN achieved the best overall segmentation performance, obtaining 89.89% mean Average Precision, 96.88% precision, 89.89% recall, and a 93.26% F1 Score, demonstrating the most reliable balance between segmentation accuracy and detection performance among the evaluated models.

The findings demonstrate that integrating instance segmentation with coin-based measurement calibration, rule-based broken grain detection, Logistic regression for chalky grain identification, and LAB/HSV-based discoloration analysis can provide an effective and accessible approach for automated rice grain quality assessment using smartphone-captured images.

Keywords: Artificial Intelligence, Rice Quality Assessment, Mask R-CNN, Image Processing, Mobile Application, Grain Morphology

INTRODUCTION

Rice is a major staple food and an essential part of daily life in many countries, particularly in Asia. In the Philippines, it plays a critical role in food security, household consumption, and agricultural livelihood. Because rice is widely consumed and traded, its quality significantly influences consumer preference, market value, and overall acceptability. Grain characteristics such as size, shape, uniformity, and visible defects, including broken, chalky, and discolored grains, are commonly used indicators in evaluating rice quality.

Despite its importance, assessing rice quality remains challenging for ordinary consumers. Conventional methods typically rely on manual inspection by trained personnel or laboratory-based procedures using specialized equipment. While these methods can provide reliable results, they are often time-consuming, costly, and impractical in everyday purchasing situations. As a result, consumers frequently depend on subjective visual judgment or seller-provided information, which may lead to inconsistent evaluation.

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With the increasing availability of smartphones and advancements in computer vision and artificial intelligence, image-based quality assessment has become more feasible for consumer-oriented applications. These technologies enable the analysis of grain features through digital images, offering a more accessible and objective approach to inspection.

This study introduces *Grainalyze*, a mobile-based application designed to assist in rice grain quality assessment through image analysis. The system focuses on identifying visible grain characteristics and defects from smartphone-captured images under controlled conditions. By integrating mobile technology with artificial intelligence, the application aims to provide a practical and consistent method for evaluating rice quality.

This study supports Sustainable Development Goal 2: Zero Hunger by promoting improved food quality awareness and contributes to Sustainable Development Goal 9: Industry, Innovation and Infrastructure and Sustainable Development Goal 12: Responsible Consumption and Production by encouraging accessible and informed decision-making [18].

METHODS

A. Conceptual Framework

To provide a structured representation of the study workflow, a conceptual framework was developed to illustrate the sequence of processes involved in the Grainalyze application. The framework presents how rice grain images are captured, processed, analyzed, and translated into quality assessment results, as well as how information flows across each stage of the system.

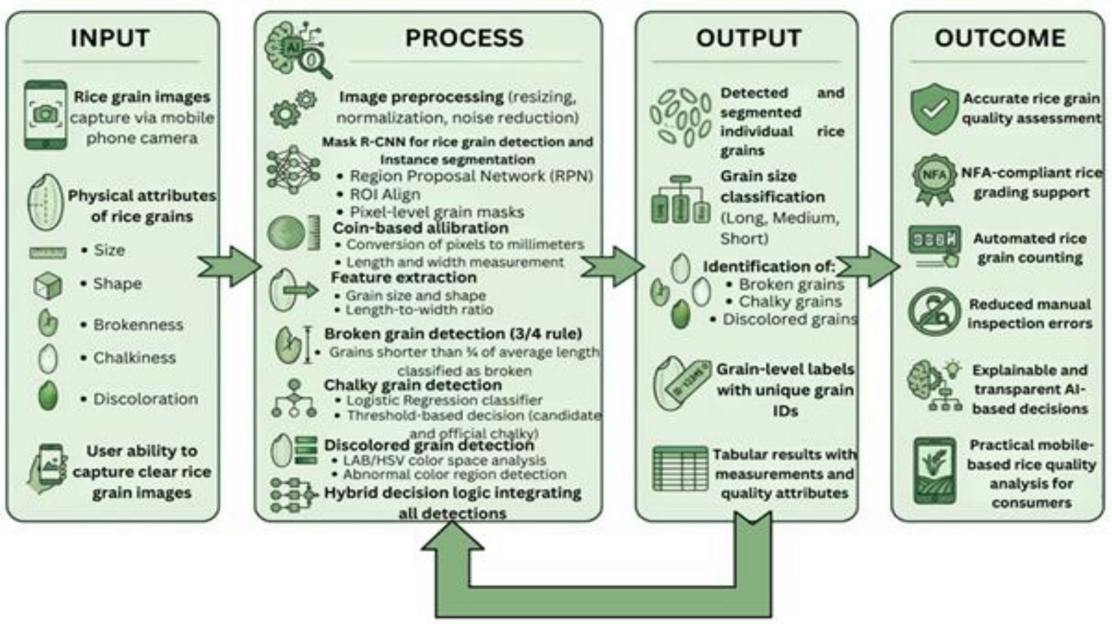

Figure 1. Conceptual Framework

The input stage begins with the acquisition of rice grain images using a mobile device under controlled conditions. A reference object, such as a coin, is included in the image to enable calibration and ensure accurate measurement of grain dimensions.

During the processing stage, the images undergo preprocessing techniques, including resizing, normalization, and noise reduction, to enhance image quality and consistency. Instance segmentation is then performed using the Mask R-CNN model, which utilizes a Region Proposal Network (RPN) and ROI Align to accurately detect and isolate individual grains. Extracted features such as grain size and shape are subsequently used for further analysis. Defect detection is carried out using a combination of rule-based methods, Logistic Regression for chalky grain identification, and LAB/HSV color analysis for detecting discoloration.

The output stage generates segmented grain images, grain size classifications, and identified defects. These outputs are then translated into an overall rice quality assessment, providing users with an accessible and objective evaluation of grain quality.

Overall, the conceptual framework provides a clear and comprehensive representation of how the Grainalyze application integrates image processing, deep learning, and classification techniques to perform rice grain quality assessment. By structuring the workflow from image acquisition to output generation, the framework demonstrates how raw input data are transformed into meaningful and interpretable results. This approach supports the development of a reliable, efficient, and accessible tool for evaluating rice grain quality using mobile-based technology.

B. Dataset Collection and Preparation

Rice grain images were collected from multiple sources and developed in accordance with established rice quality standards, particularly the Philippine National Standards of the Bureau of Agriculture and Fisheries Standards (PNS:BAFS) and CODEX guidelines. The dataset preparation was further guided by the National Food Authority (NFA), ensuring that the collected samples and classification categories are consistent with actual grain inspection and evaluation practices.

The dataset consists of four grain quality categories: whole, broken, chalky, and discolored grains. A total of 3,885 source images were used, all of which were annotated at the grain level using Roboflow to support instance segmentation.

The dataset was partitioned into training, validation, and testing sets, consisting of approximately 3,100 images (80%) for training, and 380 images (10%) each for validation and testing. This distribution ensures balanced model training, hyperparameter tuning, and unbiased performance evaluation.

Preprocessing operations were applied to standardize the input data. All images were automatically oriented and resized to a resolution of 640 × 640 pixels. Pixel values were normalized to reduce variations caused by lighting conditions. Noise reduction was achieved through controlled image acquisition and normalization, minimizing the effects of uneven illumination, shadows, and background interference.

To improve model robustness and generalization, data augmentation techniques were applied. These include horizontal and vertical flipping, 90° rotations (clockwise, counterclockwise, and upside down), slight rotational variations (−1° to +1°), zoom scaling (0% to 20%), brightness adjustment (−5% to +5%), and minor blurring of up to 1 pixel. These transformations simulate real-world variations in image capture conditions and help prevent overfitting during training.

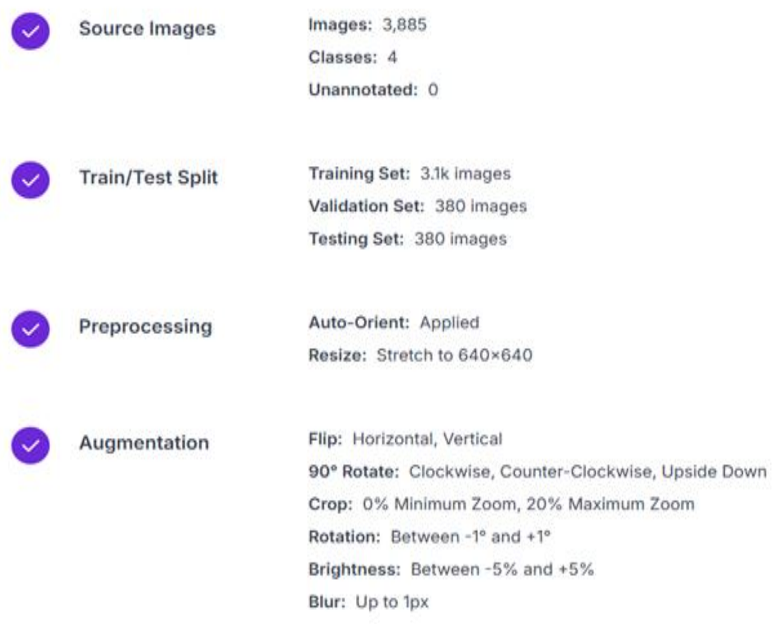

Figure 2. Roboflow Preprocessing and Augmentation Configuration

C. Model Selection and Training

Multiple deep learning models were considered for rice grain segmentation, including Mask R-CNN, YOLOv8n-seg, YOLOv8s-seg, and U-Net. These models were selected based on their capability to perform object detection and instance segmentation tasks, which are essential for accurately identifying and isolating individual rice grains.

All models were trained using the same dataset and preprocessing pipeline to ensure consistency and comparability. Model training was conducted using Python in a cloud-based environment through Google Colab, utilizing an NVIDIA L4 GPU to accelerate computation.

The Detectron2 framework was used to implement the Mask R-CNN model, while other supporting libraries were utilized for training and evaluation of the remaining models. The dataset was divided into training (80%), validation (10%), and testing (10%) sets.

Following segmentation, additional processing techniques were applied to analyze grain characteristics and identify defects. Grain size measurement was performed using a coin-based reference included in the captured images, allowing for real-world calibration of grain dimensions. Broken grain detection was implemented using the ¾ rule, where grains with lengths less than 75% of the average grain length were classified as broken.

For defect classification, a Logistic Regression model was utilized to identify chalky grains based on extracted visual features. Discolored grains were detected using color space analysis in LAB and HSV formats, enabling the identification of abnormal pigmentation and variations in grain color.

Key hyperparameters, including learning rate, batch size, and optimizer type, were configured and adjusted to ensure stable training and optimal model performance.

D. Performance Evaluation Metrics

To evaluate the performance of the trained models, a set of standard quantitative metrics was employed to measure both classification accuracy and segmentation capability. These metrics were derived by comparing the predicted outputs of the models, including segmented grain regions and corresponding class labels, with the annotated ground truth data. This evaluation approach ensures that both detection accuracy and classification reliability are systematically assessed.

The primary metric used in this study is mean Average Precision (mAP), which provides an overall measure of model performance across all grain categories. The computation of mAP is based on the precision–recall relationship and incorporates Intersection over Union (IoU) thresholds to determine the accuracy of predicted segmentation masks. A prediction is considered correct when the overlap between the predicted and ground truth regions satisfies the defined IoU threshold, ensuring that both localization and classification are taken into account.

In addition to mAP, classification-based metrics such as accuracy, precision, recall, and F1-score were utilized to provide a more detailed evaluation of model performance. Accuracy measures the overall correctness of the model, while precision reflects the reliability of positive predictions. Recall evaluates the ability of the model to correctly identify all relevant grain instances, and the F1-score provides a balanced measure by combining precision and recall.

These evaluation metrics are mathematically defined as follows:

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

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

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

$$F1 = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$$

where:

TP represents true positive predictions,

FP represents false positive predictions,

FN represents false negative predictions, and

TN represents true negative predictions.

Overall, these metrics provide a consistent and objective basis for evaluating model performance and enable effective comparison of different models used in the study.

RESULTS AND DISCUSSIONS

A. System Interface

The Grainalyze system consists of a web-based dashboard for administrators and a mobile application interface for end users, enabling efficient rice grain analysis and result visualization across different user roles.

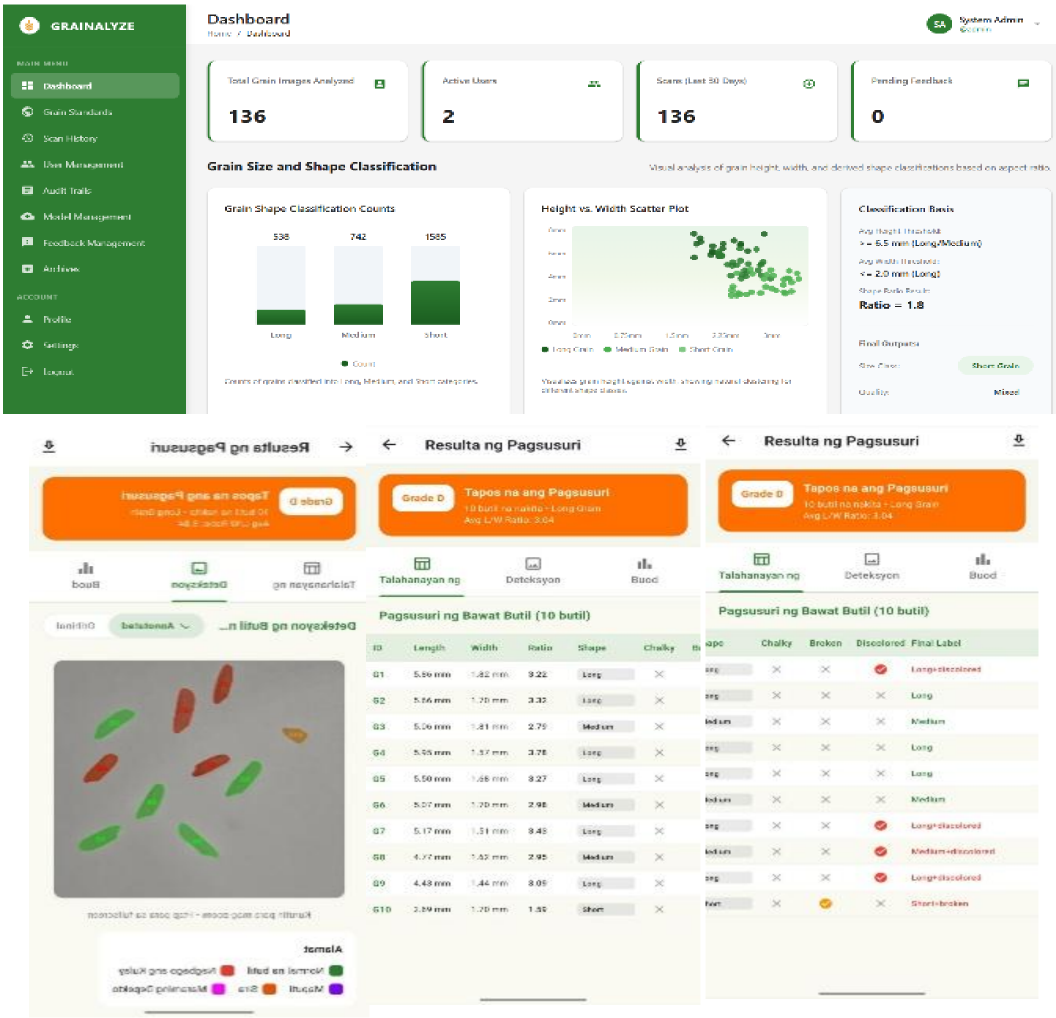

Figure 3. Grainalyze Mobile Application and Web Interfaces

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The web-based dashboard is designed for administrative use, providing an overview of system activity and analysis results. It displays key information such as the total number of grain images analyzed, active users, and scan records. In addition, graphical summaries, including grain size and shape classification distributions, are presented to support monitoring and data analysis. This interface allows administrators to efficiently manage system data, review outputs, and monitor overall system performance.

The mobile application, on the other hand, is intended for end users and focuses on image-based rice grain analysis. Users can capture or upload images of rice grains, which are then processed by the system. The output displays segmented grain images, where individual grains are highlighted using color-coded overlays based on their classification, such as whole, broken, chalky, and discolored.

The application also provides a detailed tabular view of results, including grain-level attributes such as length, width, aspect ratio, and classification labels. Additional defect indicators, such as chalkiness and discoloration, are presented for each grain. Summary outputs, including overall grain quality grading and classification counts, are also displayed to provide a comprehensive assessment.

The integration of an administrative dashboard and a user-focused mobile application demonstrate the system's capability to support both data management and practical usage. This dual-interface design enhances accessibility and usability, allowing efficient monitoring by administrators and convenient quality assessment for end users.

B. Comparative Model Performances

The performance of the evaluated models was compared using standard metrics, including mean Average Precision (mAP), AP50, AP75, precision, recall, and F1-score. A visual comparison of the results is presented in Figure 4, while the corresponding numerical values are summarized in Table 1.

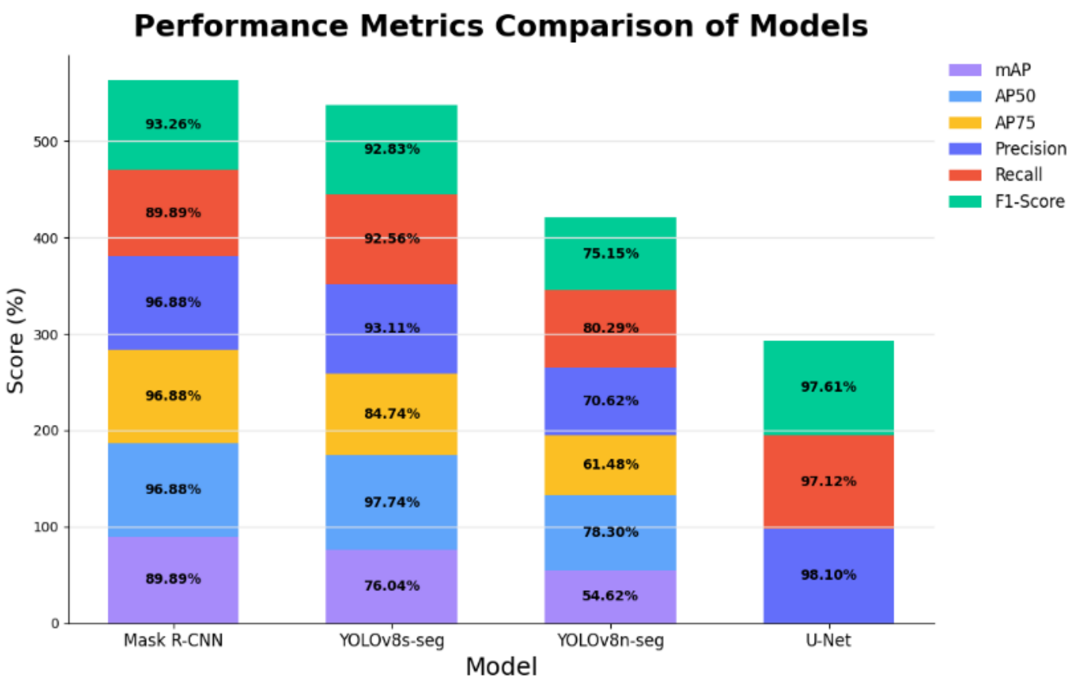

Figure 4. Performance Metrics Comparison of Models

Table 1. Model Performance Results

Model	mAP	AP50	AP75	Precision	Recall	F1-Score
Mask R-CNN	89.89	96.88	96.88	96.88	89.89	93.26
YOLOv8s-seg	76.04	97.74	84.74	93.11	92.56	92.83
Yolov8n-seg	54.62	78.30	61.48	70.62	80.29	75.15
U-Net	N/A	N/A	N/A	98.10	97.12	97.61

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The results indicate that Mask R-CNN achieved the most consistent and balanced performance across all evaluation metrics. It obtained high scores in mAP, AP50, and AP75, demonstrating strong capability in accurately detecting and segmenting individual rice grains under varying Intersection over Union (IoU) thresholds. Its precision, recall, and F1-score further confirm the reliability and stability of its predictions.

YOLOv8s-seg also demonstrated competitive performance, particularly in AP50, precision, and recall, indicating effective detection capability at lower IoU thresholds. However, its performance decreased at higher thresholds (AP75), suggesting limitations in achieving precise segmentation compared to Mask R-CNN. YOLOv8n-seg, being a lightweight variant, exhibited lower performance across most metrics, reflecting the trade-off between computational efficiency and accuracy.

U-Net achieved high precision and recall values; however, it is limited in the context of instance segmentation. As a semantic segmentation model, it lacks the ability to distinguish individual grain instances, which affects its applicability for tasks requiring object-level analysis such as grain counting and measurement.

Overall, the comparative analysis shows that Mask R-CNN provides the most suitable approach for rice grain quality assessment, as it effectively combines accurate instance segmentation with reliable classification performance. The detailed values presented in Table 1 further support the trends observed in

C. Training Loss Curve

The training performance of the selected model was evaluated using loss curves, which illustrate the learning behavior of the model over training epochs. The training and validation loss values were monitored to assess convergence and detect potential overfitting or underfitting during the training process.

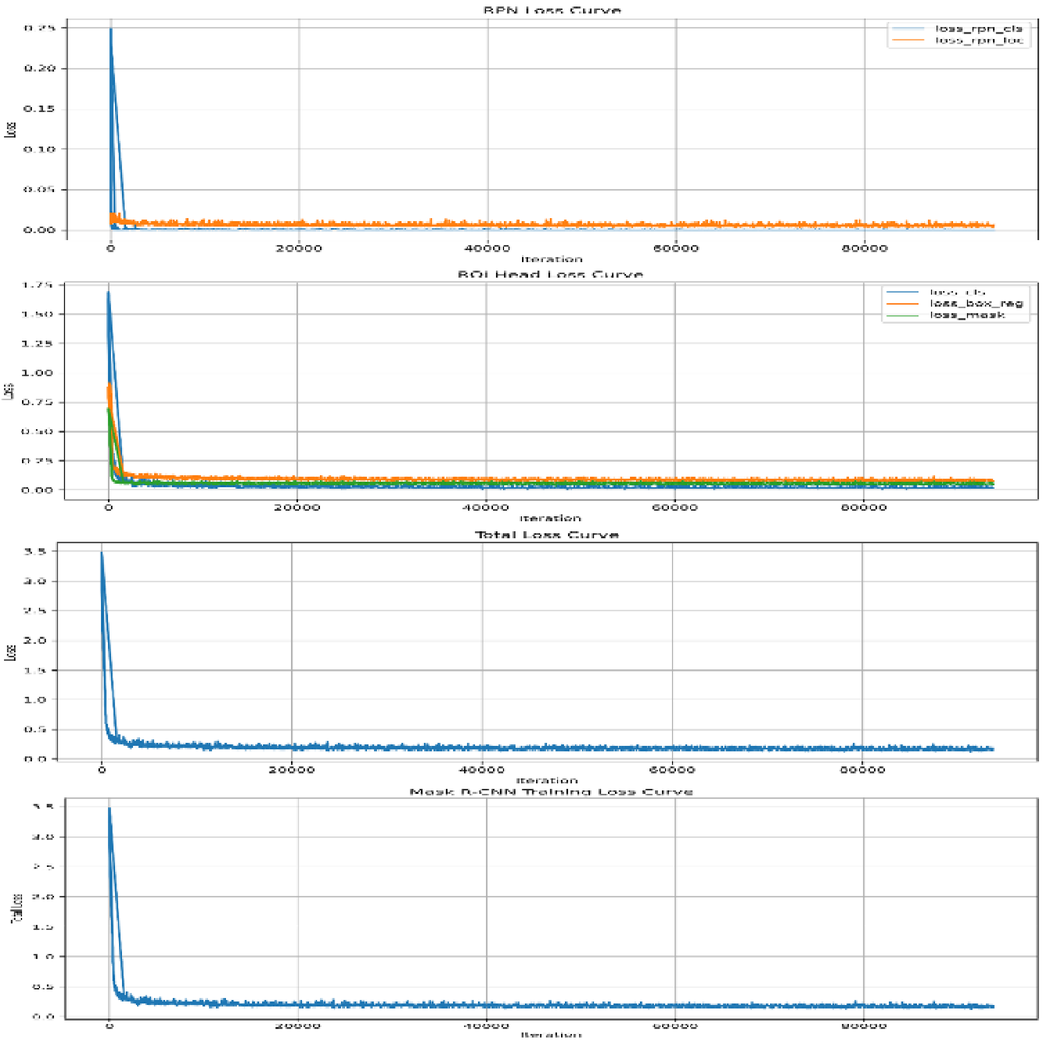

Figure 5. Mask R-CNN Training Loss Curve

The results show that both training and validation loss exhibit a decreasing trend as the number of epochs increases, indicating that the model effectively learns the underlying features of the dataset. The gap between training and validation loss remains relatively small, suggesting that the model generalizes well to unseen data and does not suffer from significant overfitting.

Minor fluctuations in the loss values were observed during training, which are expected due to variations in batch data and optimization dynamics. However, the overall stability of the curves demonstrates consistent learning behavior and convergence of the model.

These observations confirm that the selected model was trained effectively and is capable of achieving stable performance for rice grain segmentation and classification tasks.

D. Confusion Matrix Analysis

The classification performance of the selected model was further evaluated using confusion matrices to analyze its ability to distinguish between different rice grain categories. Both raw and normalized confusion matrices were utilized to provide a comprehensive assessment of prediction behavior.

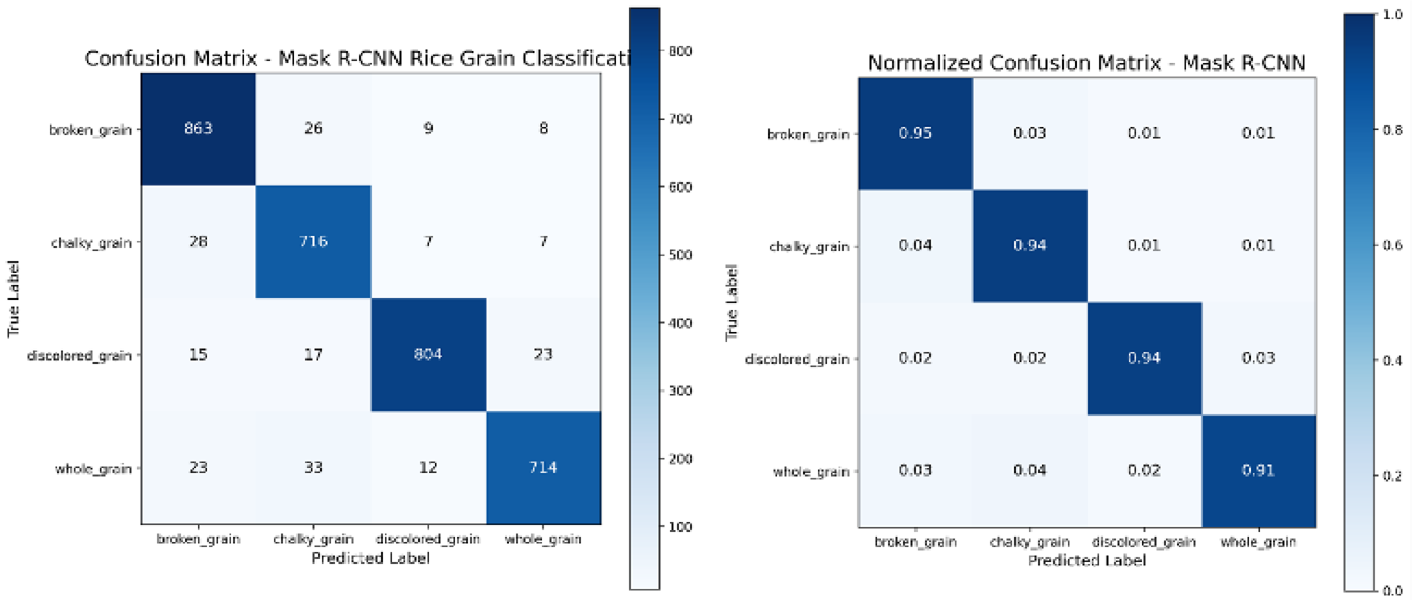

Figure 6. Raw and Normalize Confusion Matrices

The raw confusion matrix shows the absolute number of predictions for each class, including broken, chalky, discolored, and whole grains. High values along the diagonal indicate correct classifications, with the model accurately identifying the majority of samples across all categories. For instance, a large number of broken, chalky, discolored, and whole grains were correctly classified, demonstrating strong model performance.

The normalized confusion matrix provides a clearer interpretation by expressing the results in terms of proportions. The model achieved approximately 95% accuracy for broken grains, 94% for chalky grains, 94% for discolored grains, and 91% for whole grains. These values indicate that the model performs consistently well across all classes.

Minor misclassifications are observed in off-diagonal values, particularly between visually similar categories such as whole and broken grains, as well as chalky and discolored grains. These errors can be attributed to overlapping visual features, including similarities in shape, texture, and color intensity.

Overall, the confusion matrix results demonstrate that the model achieves high classification accuracy with minimal errors. The strong diagonal dominance in both raw and normalized matrices confirms the reliability of the model in distinguishing different rice grain conditions, supporting its effectiveness for grain-level quality assessment.

E. Coco Evaluation Metrics

The performance of the selected Mask R-CNN model was further evaluated using COCO-style metrics to assess both detection and segmentation accuracy. These metrics include Average Precision (AP), AP50, AP75, AP for small objects (APs), and AP for medium objects (APm), computed for both bounding box (bbox) and segmentation (segm) outputs.

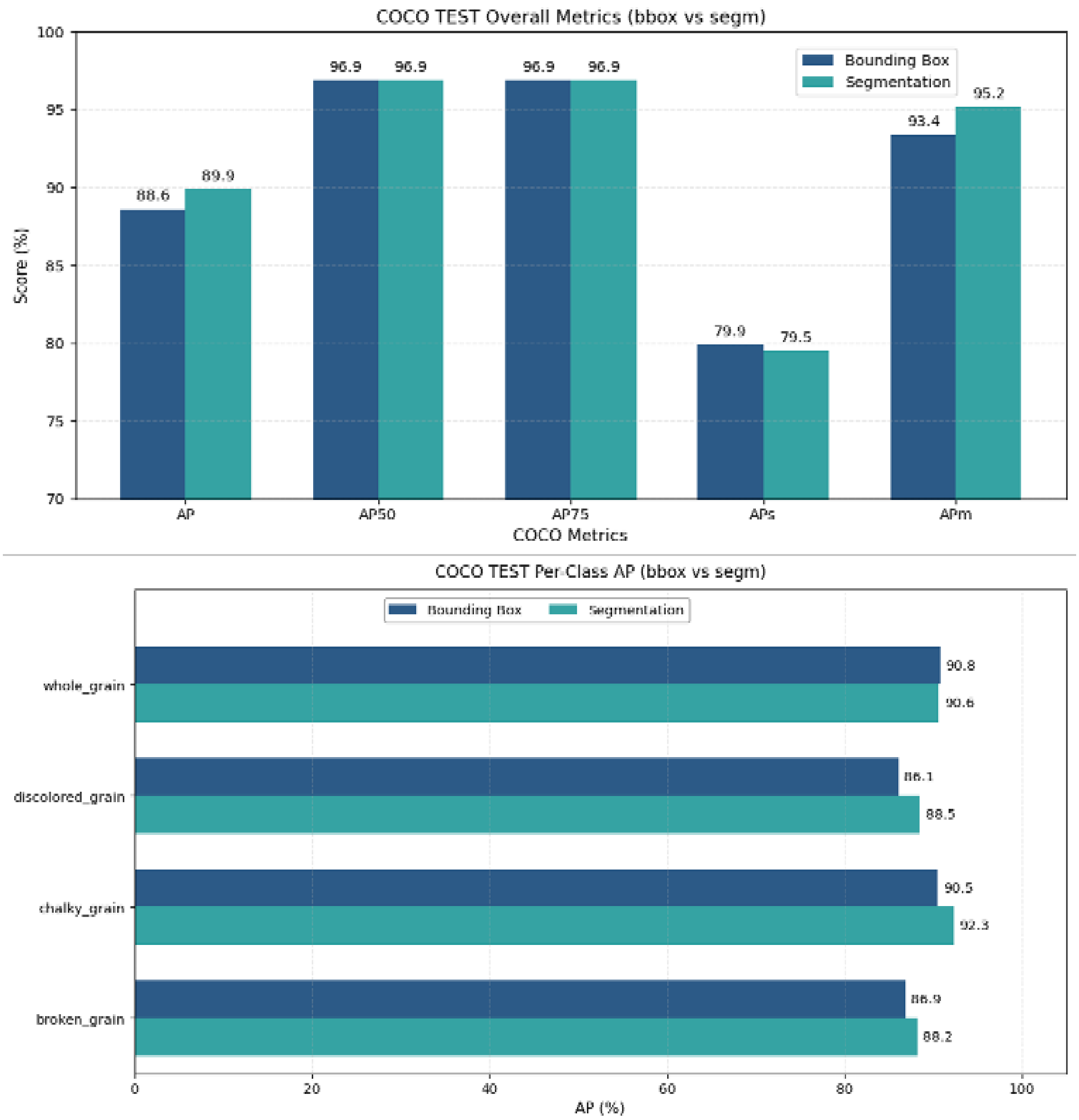

Figure 7. Coco Test Overall and Per-Class Metrics

The overall results show that the model achieved high performance across both detection and segmentation tasks. For bounding box evaluation, the model obtained an AP of 88.6%, AP50 of 96.9%, and AP75 of 96.9%. Similarly, segmentation performance yielded an AP of 89.9%, AP50 of 96.9%, and AP75 of 96.9%. These results indicate that the model maintains strong accuracy even at higher IoU thresholds, demonstrating its capability for precise localization and segmentation of rice grains.

In terms of object scale, the model achieved an AP of 79.9% (bbox) and 79.5% (segm) for small objects, and 93.4% (bbox) and 95.2% (segm) for medium-sized objects. This suggests that the model performs more effectively on medium-sized grains, while slightly lower performance is observed for smaller grain instances due to limited feature visibility.

The per-class evaluation further confirms consistent model performance across all grain categories. For whole grains, the model achieved 90.8% (bbox) and 90.6% (segm). Discolored grains obtained 86.1% (bbox) and

88.5% (segm), while chalky grains reached 90.5% (bbox) and 92.3% (segm). Broken grains recorded 86.9% (bbox) and 88.2% (segm). These results indicate that segmentation performance is generally comparable to or slightly higher than bounding box detection across most classes.

Overall, the COCO evaluation metrics demonstrate that the Mask R-CNN model achieves high accuracy in both detection and segmentation tasks. The consistent performance across different IoU thresholds and grain categories highlights the robustness of the model for rice grain quality assessment. These results further support the effectiveness of the model in providing reliable grain-level analysis for practical applications.

DISCUSSION OF FINDINGS

The results of the study demonstrate that the integration of deep learning, image processing, and rule-based techniques provides an effective approach for rice grain quality assessment. The use of Mask R-CNN for instance segmentation enabled accurate detection and separation of individual rice grains, which is essential for extracting grain-level features such as size, shape, and defects.

The comparative analysis showed that Mask R-CNN outperformed other evaluated models due to its ability to perform precise instance segmentation. Unlike lightweight and semantic segmentation models, Mask R-CNN maintains high accuracy across different evaluation metrics, particularly in terms of mAP and segmentation performance. This capability allows the model to handle complex grain arrangements and overlapping instances more effectively.

The confusion matrix results further confirm the model’s strong classification performance, with high accuracy across all grain categories and minimal misclassification. Errors were primarily observed between visually similar classes, such as whole and broken grains, as well as chalky and discolored grains. These challenges are expected due to overlapping visual characteristics, including similarities in texture and color.

The COCO evaluation metrics demonstrate that the model maintains high performance across different IoU thresholds and grain categories. The model also showed better performance on medium-sized objects compared to smaller ones, indicating that object scale influences detection accuracy. Despite this, the model still achieved reliable results across all grain types.

In addition, the integration of rule-based methods, Logistic Regression for chalky grain identification, and LAB/HSV color analysis for discoloration detection contributed to the overall effectiveness of the system. This hybrid approach enhances the model’s ability to capture both structural and visual characteristics of rice grains.

Overall, the findings indicate that the proposed approach provides a reliable and efficient solution for rice grain quality assessment. The system is capable of delivering accurate, consistent, and interpretable results, making it suitable for practical applications such as consumer-level grain evaluation and quality monitoring.

CONCLUSION

This study presented Grainalyze, a hybrid artificial intelligence-based system for rice grain quality assessment using image processing and instance segmentation techniques. The system integrates Mask R-CNN with a ResNet-50 and Feature Pyramid Network (FPN) backbone, together with rule-based classification and color analysis, to accurately identify rice grain conditions such as whole, broken, chalky, and discolored grains.

The results demonstrated that the Mask R-CNN model achieved the most consistent and reliable performance among the evaluated models, with high precision, recall, and F1-score. The use of a Region Proposal Network (RPN) and ROI Align enabled accurate detection and segmentation of individual rice grains, which is essential for detailed morphological analysis.

Furthermore, the integration of domain-specific techniques such as coin-based calibration for size measurement, the ¾ rule for broken grain detection, and LAB/HSV color analysis for discoloration enhanced the overall classification performance. These findings are consistent with previous studies that emphasize the effectiveness of combining deep learning and image processing techniques in agricultural applications [1], [7], [20].

The developed system provides a practical and accessible approach for rice quality evaluation at the consumer level. Although implemented as a prototype, the system demonstrates strong potential for real-world application and scalability.

Future work may focus on expanding the dataset, improving model optimization, and deploying the system as a fully functional mobile application capable of real-time rice grain quality assessment.

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