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Classification and Morphology Detection of Rice Using Machine Vision and Deep Learning

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Abstract. Rice is a critical component of the world's food supply chain. It is consumed after milling, but the milling process significantly impacts rice quality, with broken grains posing a major challenge for the industry. Traditional quality assessment methods, such as manual inspection, are inefficient and inconsistent, necessitating advanced solutions for accurate classification and morphological analysis. This paper presents an AI-driven machine vision system leveraging the You Only Look Once version 8 (YOLOv8) deep learning model to automate real-time rice quality assessment. A custom dataset of rice grain images was collected, preprocessed, and used to train the model for morphological feature extraction and kernel classification. Morphological features such as shape, size, and colour are extracted to evaluate milling yield, while classification assigns each grain to one of three categories: Good Rice, Broken Rice, or Brown Rice. Experimental results demonstrate the system's robustness, achieving 98% classification accuracy and precise morphological analysis. The model also generates statistical data for condition monitoring and fault detection. By integrating deep learning with machine vision, this approach enables fast, consistent, and automated quality control, reducing human intervention and standardising rice milling processes. The system's industrial applicability lies in its ability to enhance efficiency, minimise waste, and ensure compliance with global quality standards.

Keywords: Measurement automation, Real-time quality inspection, AI-based classification, Machine vision in food robotics, Visual metrology.

1 Introduction and Background

Rice is a staple food for over half of the world's population [1], particularly in Asia and Africa, where it plays a crucial role in both nutrition and economy. The quality of rice is paramount, as it directly influences consumer preferences and market prices. Traditional methods of rice classification rely heavily on human expertise, which can be subjective and prone to errors. Visual grading is influenced by individual judgment, leading to inconsistent results. Other factors, such as fatigue and experience level, can impact classification accuracy. This method is time-consuming, labour-intensive and cannot provide instant quality metrics in real time. The need for efficient and accurate classification methods has led to the exploration of automated systems that leverage advanced technologies. The classification of rice grains based on morphological characteristics, such as size, shape, and colour, is essential for ensuring quality control and maintaining consumer trust [2]

Accurate rice classification is vital for several reasons. It aids in identifying different rice varieties, which can have distinct culinary properties and market values. For instance, rice is categorised into long-grain, medium-grain, and short-grain types, each appealing to different consumer preferences [3]. Furthermore, morphology detection is crucial for assessing rice quality, including identifying defects such as chalkiness, discolouration, and broken grains. These factors significantly impact marketability and can lead to economic losses if not properly managed [4]. Developing a robust real-time classification system that can automate this process making it essential for enhancing efficiency in the rice milling industry.

Machine vision and deep learning have emerged as transformative technologies in various industrial applications, including the food industry. Machine vision systems utilise digital imaging to capture and analyse visual information, enabling automated inspection, classification of products and process optimisation [5]. In the context of rice classification, machine vision facilitates the extraction of morphological features from rice grains, which are critical for accurate classification. Deep learning, particularly You Only Look Once (YOLOv8), has shown remarkable success in image recognition tasks due to its ability to learn complex patterns and features from large datasets [6]. The integration of these technologies allows for the development of robust classification systems that operate with high accuracy, efficiency, and further provide additional data for condition monitoring and fault detection.

Previous studies have employed various machine learning techniques, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and artificial neural networks (ANN), to classify rice grains based on morphological features such as shape, size, and colour [7]. However, these methods often struggle with the high similarity between different rice varieties, resulting in lower classification accuracy [6]. For example, in [7], a maximum classification accuracy of 92.3% was achieved using an ANN, but this was effective for distinct rice types.

Despite the advancements in deep learning for rice classification, several research gaps remain. Many existing studies focus on a limited number of rice diseases or varieties, often using datasets that do not reflect the diversity found in real-world food industry settings [8]. Additionally, while some research has explored the use of transfer learning and hybrid models, there is still a lack of comprehensive studies that integrate multiple deep learning architectures to enhance classification performance across various conditions [9].

Prior research in rice morphological analysis has been limited to offline methods requiring manual grain separation to prevent contact between kernels, a process that can disrupt real-time milling conditions. Previous AI approaches often fail to distinguish touching grains and may erroneously classify clustered kernels as single entities. Utilising the YOLOv8 instance segmentation model, the study enables real-time object detection, analysis of rice morphology, distinguishing touching grains, and accurately classifying each kernel. It further provides numerical data for quality monitoring and fault detection.

1.1 Contributions of This Study

This study proposes a real-time automated framework for AI-driven quality assessment of rice grains during milling operations, aiming to enhance the quality monitoring of milled rice products. The key contributions of this work are as follows:

- **Development of a Comprehensive Dataset:** A GigE vision camera was used to capture rice images under industrial milling conditions. The images were preprocessed and annotated with instance segmentation masks, enabling precise extraction of physical parameters such as grain shape, size, and colour.
- **Evaluation of Classification Performance:** Instance segmentation masks were employed to address the challenge of touching grains, which traditional methods often misclassify as single entities. The proposed YOLOv8-based pipeline integrates morphological feature extraction with statistical classification for continuous monitoring of rice quality classes (Good Rice, Broken Rice, and Brown Rice) and defect detection (Fig. 8).
- **Novelty Compared to Previous YOLO-Based Approaches:** Unlike prior YOLO-based rice classifiers, this study introduces a combined framework of YOLOv8 instance segmentation with morphological and statistical analysis. This integration not only improves grain-level detection accuracy but also provides quantitative milling yield metrics in real time.
- **Practical Implications for the Rice Milling Industry:** This study proposes a real-time automated approach to assess rice grain quality during the milling process. Such integration supports better decision-making, operational optimisation, and consistent product quality.

In summary, this study introduces a novel integration of YOLOv8 instance segmentation with morphological and statistical analysis for automated rice grain quality assessment. The approach enhances grain detection and rice segmentation in food production, enabling real-time deployment and delivering both classification insights and numerical data for process monitoring. The methodology advances the application of AI in food industry automation and quality control.

2 Materials and Methods

2.1 Sample Preparation

The present study employed deep learning models to detect the quality of Italian Carnaroli rice, renowned for its culinary versatility. To perform this analysis, a dataset consisting of a mixture of approximately 85% high-quality rice, 10% broken rice, and a minor fraction of 5% brown rice was utilised (Fig. 1). This random representation was selected to mimic real-time conditions and enable a comprehensive assessment of the model's performance. Various pre-processing techniques, such as rotation, contrast adjustment, flipping, and noise inclusion, were applied to enhance the model's ability to distinguish high-quality rice from broken rice.

(a) Good rice (b) Brown rice (c) Broken rice

Fig. 1: Different types of rice used in this study. From left to right: Good rice, Brown rice, and Broken rice.

2.2 Data Acquisition

A custom-designed bench-top image acquisition system was set up for controlled image acquisition (Fig. 2). The system was composed of a variable-speed conveyor, which was operated at a speed of 10 cm/s to ensure a steady and uniform distribution of rice grains. The GigE Vision camera was positioned above the belt, capturing high-resolution images at 1920 x 1080 pixels. The setup also consisted of a feeder to dispense rice grains uniformly. This system interfaced with a personal computer for image capture and display. To ensure consistent illumination, adjustable LED lights were positioned above the samples. A dark background conveyor enhanced contrast and facilitated the segmentation process (Fig. 2.)

2.3 Deep Learning Architecture (YOLOv8)

In this study, the YOLOv8n-seg architecture was specifically chosen for its efficiency and adaptability in real-time classification and segmentation of rice grains. This model integrates advanced techniques in object detection and instance segmentation to accurately distinguish whole, broken, and brown rice grains. YOLOv8, developed by the same researchers behind YOLOv5, shares a similar stylistic approach but incorporates notable advancements and optimisations over its predecessor. According to [11], YOLOv8 demonstrates enhanced algorithmic performance.

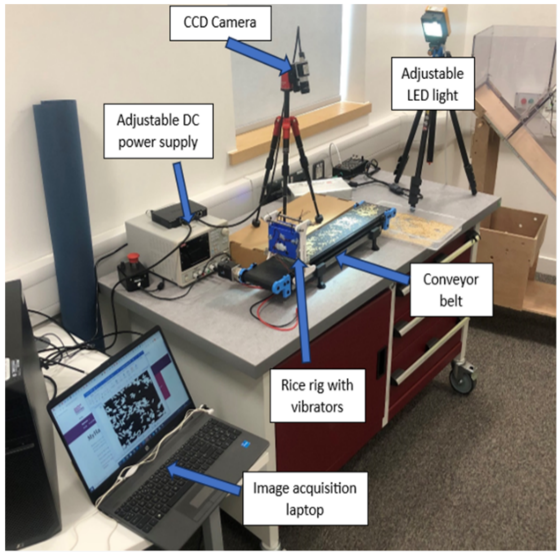


Fig. 2: Experimental setup for rice acquisition used in this study.

Model Selection and Justification: Choosing the right AI model is crucial for computer vision projects. Ultralytics YOLOv8 is a highly popular model for object detection. It introduces architectural improvements and new features aimed at enhancing both accuracy and efficiency. This study was based on the modified architecture structure of Ultralytics [10].

Enhanced mAP Performance: YOLOv8 demonstrates superior performance compared to its predecessors, including YOLOv7 and YOLOv6, as shown in Fig. 3 [10], achieving a mean Average Precision (mAP) of 53.9% (YOLOv8x) on the COCO dataset. This high precision makes it highly suitable for fine-grained classification of rice grains.

Optimised Speed and Latency: The model is capable of achieving detection speeds as low as 0.99 milliseconds per image (YOLOv8n) on high-performance GPUs, facilitating real-time processing. This efficiency renders it particularly well-suited for industrial-scale applications.

Compact Architecture with Enhanced Efficiency: YOLOv8 optimally balances computational complexity and accuracy, featuring parameter sizes of 11.2M (YOLOv8s) and 25.9M (YOLOv8m). This efficient design enables deployment on resource-constrained edge devices while maintaining high-performance capabilities.

Comparison with Other Models: YOLOv8 exhibited superior performance compared to YOLOv5, YOLOv7, and EfficientDet in terms of both detection speed and accuracy. Compared to EfficientDet, which has higher latency, YOLOv8 demonstrated faster detection, making it more suitable for real-time industrial

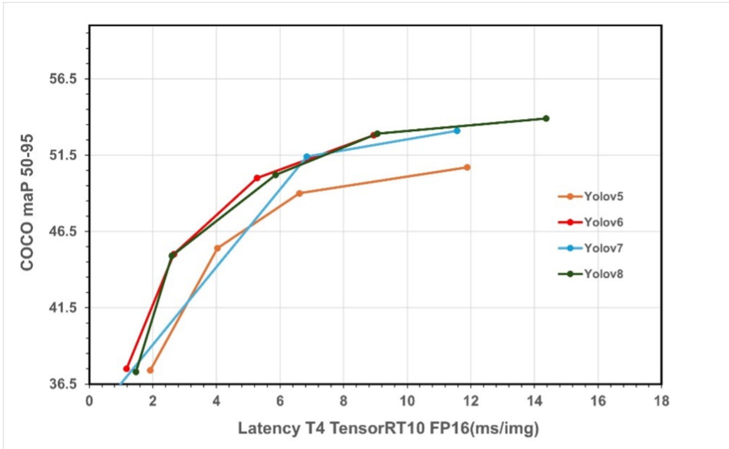


Fig. 3: Performance Metrics

applications. Models such as PP-YOLOE+ and YOLOX achieved relatively lower mean Average Precision (mAP), further validating YOLOv8's superior capability in fine-grained rice grain classification [10].

Network Architecture: The YOLOv8 model follows a structured architecture comprising a backbone, neck, and head, each designed to optimise feature extraction, aggregation, and final predictions. The backbone extracts multi-scale features using convolutional layers (Conv) and Cross-Stage Partial Networks (C2f), which enhance gradient propagation and reduce computational overhead, while the neck aggregates features across multiple scales, improving detection robustness and facilitating effective object representation. The head is responsible for classification, localisation, and segmentation by generating bounding boxes, confidence scores, and class probabilities.

Training Procedure: The model was trained using labelled rice images (Fig. 4b), using the YOLOv8n instance segmentation model. (Fig. 4a) shows a sample of raw data used for labelling. Mixed-precision training was employed, utilising both 16-bit floating point (FP16) and 32-bit floating point (FP32) arithmetic (FP16/FP32) to enhance computational efficiency and optimise memory utilisation. Additionally, Hyperparameter optimisation was conducted to maximise classification accuracy, including tuning learning rate, batch size, and weight decay.

Evaluation Metrics: The performance of the trained YOLOv8 models in distinguishing good rice, broken rice, and brown rice, was evaluated using multiple metrics, including precision 1, and recall 2 assessing classification accuracy, the

(a) Unlabelled Rice

(b) Labelled rice

Fig. 4: Comparison of labelled(b) and unlabelled (a) rice kernel images to be used for instance segmentation.

F1-score 3 to balance precision and recall, inference speed to determine real-time detection feasibility, and a confusion matrix to identify misclassification and refine decision boundaries.

1. Precision measures the model's ability to avoid false positives:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

where TP = True Positives and FP = False Positives. High precision indicates fewer misclassifications.

2. Recall quantifies the model's sensitivity in detecting all relevant instances:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

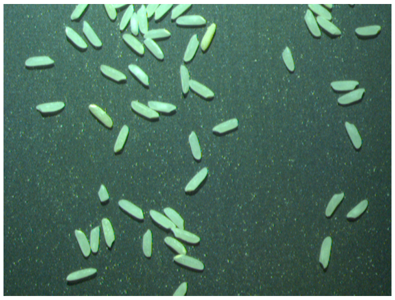
where FN = False Negatives. High recall ensures minimal undetected grains.

3. F1-Score balances precision and recall as their harmonic mean:

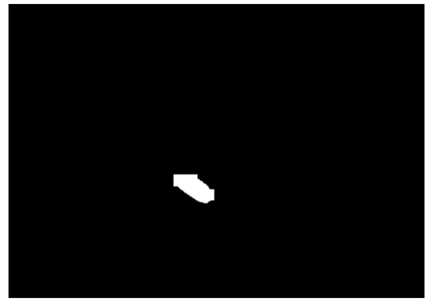
$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

2.4 Rice Morphology Detection Method

Rice grain morphology detection was performed using the YOLOv8n-segmentation model. This model segmented individual rice grains as shown in (Fig. 5b), from the background of (Fig. 5a), and classified them into Good Rice, Broken rice, and Brown Rice. The segmentation outputs enabled detailed morphological analysis, ensuring accurate characterisation of each grain.



(a) Original Image



(b) Image Processing

Fig. 5: (a) Original image (b) Binary segmentation of a single rice grain.

3 Performance Metrics and Performance Evaluation

3.1 Performance Metrics

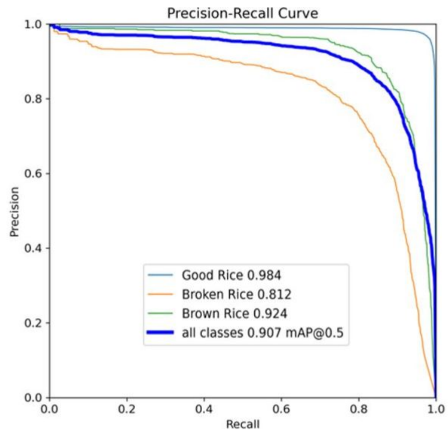
To assess the morphological characteristics of rice grains, two primary statistical approaches were utilised: mainly geometric Measurements (Length and width measurements were employed to estimate the area of each rice grain) and Pixel-Level Analysis (Leveraging pixel-level segmentation results enabled more precise grain area calculations compared to traditional geometric approximations). These statistical measures provided a comprehensive evaluation of rice grain morphology and quality, aiding in informed decision-making.

3.2 Performance Evaluation

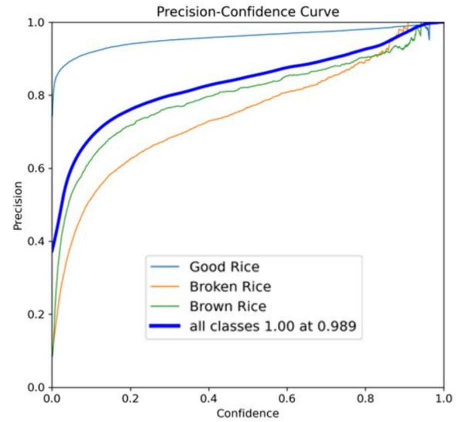
The performance of the YOLOv8 model in rice grain classification was evaluated using Accuracy, Precision 1, Recall 2, and F1-Score 3, demonstrating its effectiveness in distinguishing different rice grain types. Model Accuracy quantifies the overall correctness of the model's predictions. Based on the Precision-Recall curves, the Good Rice category exhibited the highest accuracy, with a mean Average Precision (mAP) of 0.984, while Broken Rice and Brown Rice achieved mAP scores of 0.812 and 0.924, respectively, as shown in (Fig. 6a.). The relatively lower accuracy for Brown Rice indicates challenges in detecting darker or non-standard rice grains.

In addition, as shown in (Fig. 6a.): Model Precision: Precision assesses the proportion of correctly classified rice grains among the detected samples. The Precision-Confidence curve indicates that the Good Rice class consistently maintains high precision, while the Brown Rice class demonstrates stable precision. However, Broken Rice exhibits lower precision at lower confidence thresholds compared to the other two classes.

Model Recall was applied to measure the proportion of actual rice grains correctly identified by the model. The Good Rice category achieves a recall close



(a) Precision-Recall curve



(b) Precision-Confidence curve

Fig. 6: Model performance analysis: (a) Precision-Recall curve; (b) Precision-Confidence curve.

to 1.0, indicating near-complete detection as shown in (Fig. 6b). However, the Recall-Confidence curve shows a significant decline for Broken Rice and Brown Rice, suggesting a higher rate of false negatives where these grains were not correctly detected.

4 Results and Discussion

The real-time testing demonstrated the model's robust performance in rice quality classification, particularly excelling in challenging scenarios involving grains touching, overlapping, and irregularly shaped grains, as shown in Fig. 7. Statistical condition monitoring parameters of the analysis carried out show that the system precisely classified grains into good rice (91.0%), broken rice (5.5%), and brown rice (3.6%), as shown in Fig. 8 and Fig. 9, and the result matched manual grading assessments. This AI-driven approach shows significant improvement in distinguishing good rice, broken rice, and brown rice under controlled milling conditions.

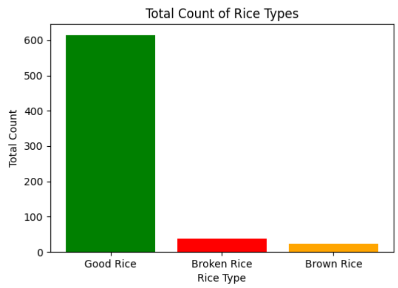


Fig. 7: Example of real-time data acquisition and analysis (Bar Chart).

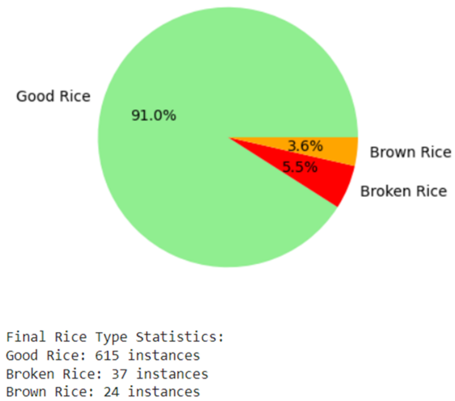


Fig. 8: Example of real-time data acquisition and analysis (Pie Chart).

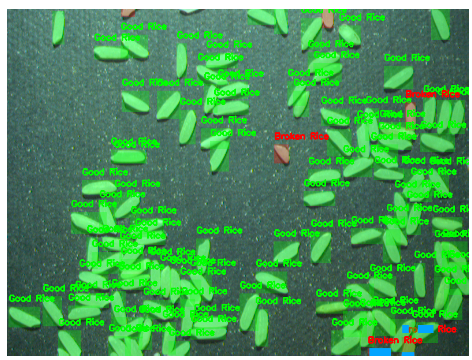


Fig. 9: Example of Real Time data acquisition and analysis.

5 Challenges and Future Work

A primary challenge in rice quality classification is class imbalance, where limited training data for Broken Rice and Brown Rice reduces model accuracy for these minority classes compared to Good Rice, prompting the need for balanced datasets with equitable representation across all categories to enhance overall performance. Additionally, the implementation requires GPU hardware for real-time performance, which may pose challenges in low-resource milling facilities.. Future work will focus on integrating this optimised technology into industrial milling systems to enable real-time process monitoring, facilitate rapid parameter adjustments, and minimise quality deviations, while also developing a single model architecture capable of accurately analysing various rice types without requiring separate models. This will significantly improve milling operational efficiency and reduce implementation complexity in the rice processing industry.

6 Conclusion

Due to the limitations of traditional methods, we have leveraged the advantage of AI technology to address these gaps. The experiment demonstrates the effectiveness of the YOLOv8 instance segmentation model in real-time monitoring and analysis of milled rice quality. The model's ability to accurately detect and classify rice grains makes it a valuable tool for automating quality control in rice milling.

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