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Deep Learning Techniques for Rice Kernel Defect Detection and Multi Classification using Yolo-V8 Model

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Abstract— In many parts of the world, rice is the main source of food, and the quality of the grain affects both consumer health and the financial interests of agricultural traders who make offers to farmers based on the quality of the rice kernels they have harvested. When trading rice, the buyer must first assess the rice's quality before deciding on the purchase price. In the past, this employment relied heavily on manual labour. Professionals are needed to hand choose and weigh various varieties of rice from samples that were chosen at random. Calculating the weight ratio of faulty rice in the total sample size is how rice grades are determined. Rice quality estimate by hand is time-consuming since skilled inspectors must recognise, pick up, and carefully weigh each defective kernel individually. This study suggests a novel approach for automatic quality estimation of rice kernels in an effort to address these issues that the existing literature is unable to address and to replace human labour-intensive operations with automated procedures. The main categories of novel rice kernel faults being detected in this initiative include broken kernels (BR), spotted kernels (SP), yellow-colored kernels (YC), mass-chalky kernels (MC), and partial-chalky kernels (PC). This experiment used a multi-stage classification strategy to do multi-classification of rice flaws, allowing a single kernel with dual defects to be discovered and then classified using Yolo v8. This approach allowed for the detection and classification of rice kernels with diverse sorts of defects.

Keywords: Rice Kernels, Convolutional Neural Network, YOLO Algorithm, Deep Learning Techniques.

I. INTRODUCTION

White rice has far less nutrients because the bran has also been removed during milling. There is a risk of beriberi, a condition brought on by thiamine and mineral deficiencies, when white rice makes up a large amount of the diet. Prior to milling, parboiled white rice is properly processed to maintain the majority of the minerals, and iron and B vitamins are added to enhanced rice. In general, deep learning for rice kernel defect detection can increase the quality and safety of rice products while lowering the costs and time of manual inspection.

II. EXISTING SYSTEM

Manual rice quality assessment is time-consuming since skilled inspectors must pick out each defective kernel individually. The machine vision was used to assess rice quality by using feature extraction which select Major axis, Minor axis, Area and eccentricity then put features to Neural Network PNN Probabilistic Neural Network model in order to train and predict rice quality, presents an assessment of grain quality emphasizing on broken rice, head rice, small broken rice, and large-sized rice discarded in rice production by Least-Square Support Vector Machine (LS-SVM) and Radius Basis Function (RBF).

2.1. Disadvantages

- Traditional rice grain classification is costly, time-consuming and requires sophisticated human expertise.
- Need for labeled data: Machine learning algorithms require large amounts of labeled data to learn from. This means that someone needs to manually label images of rice kernels as either good or defective, which can be a time-consuming and expensive process.
- The accuracy of machine learning algorithms is limited by the quality of the input images. If the images are blurry or low-resolution, it can be more difficult for the algorithm to accurately detect defects.
- Machine learning algorithms can be biased towards certain classes or features in the data, particularly
- The training data is imbalanced or contains errors.
- Lab-based instruments are costly
- Existing method is slow, labor intensive.
- Computational overhead
- Low accuracy

III. PROPOSED SYSTEM

The project's suggested solution uses deep neural networks to categorise the rice defects. The object detection technique

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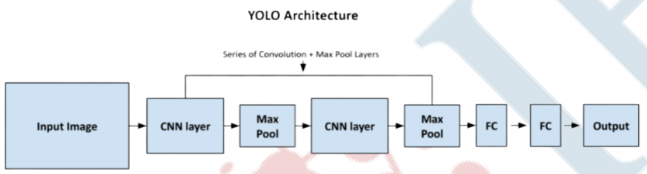
Yolov8 makes it simple to find all of the rice kernels in an image at once. Although the derived kernel position is precise, some species of rice have low categorization precision, particularly those with partial-chalky and mass-chalky kernels. As a result, we process PC and MC kernels separately using a second Yolo and a project-inspired classification network based on grayscale images. The two branches of this multi-stage work flow are separated. One is the recognition of the kernels of YC, SP, BR, and SO. The other involves localising and categorising PC and MC kernels. The outcome of the two branches is combined to create the finished product. The entire procedure is divided into five stages: kernel detection for YC, SP, BR, and SO as well as chalky kernels; segmentation; categorization of PC and MC kernels; and the stage of fusion.

3.1 YOLO Algorithm

YOLO is a method that provides real-time object detection using neural networks. This method is well-liked for its efficiency and precision. YOLO is an abbreviation for the term 'You Only Look Once'. This is an algorithm that detects and recognizes various objects in a picture (in real-time). Object detection in YOLO is done as a regression problem and provides the class probabilities of the detected images. YOLO algorithm employs convolutional neural networks (CNN) to detect objects in real-time.



The input image in this case is divided into 12.3*12.3 grids cell, with 2.4 predefined anchor boxes for each grid cell (generally used, might differ as per YOLO version). Totally we will have 1802.4 anchor boxes and each anchor box will have 82.4 predicted elements by the network as the output.

3.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a powerful class of deep learning algorithms that can be used for rice kernel defect detection. They have been widely used for rice kernel defect detection because they can automatically learn features from the input images, without the need for explicit feature engineering.

3.3. Advantages

Overall, CNN algorithms provide an efficient and accurate way to detect defects in rice kernels, helping to ensure the quality and safety of rice products.

- Rice Defect Classification and Localization can be carried out automatically and tedious manual works can be replaced.
- Classification of defected rice grains with high accuracy.
- Cost-effective, and user-friendly tool for the rapid assessment of the rice quality traits associated with consumer perception.
- This project will help the industry to certify rice without defects

IV. MODULE DESCRIPTION

4.1. Rice Defect Monitor Dashboard

The Rice Kernel Defect Detection web dashboard is an interactive web-based application that allows users to perform rice kernel defect detection using the YOLOv8 object detection algorithm and a convolutional neural network (CNN) from a web browser. The dashboard provides a user-friendly interface that enables users to upload images of rice kernels, view the detected rice kernels, and analyse the classification results for each kernel. The interface displays a graphical representation of the uploaded image with the detected rice kernels highlighted and classified according to their defect type.. It also includes features for exporting the results in various formats, such as CSV and JSON, for further analysis or integration with other systems.

4.2 Rice Defect Classifier

The Classification module for Rice Kernel Defect Detection is a machine learning model that is designed to accurately classify different types of defects in rice kernels. It is built using a Convolutional Neural Network (CNN) architecture that has been trained on a large dataset of high-resolution images of rice kernels with different types of defects, such as broken, cracked, discoloured, and insect-damaged kernels. The module has been trained on a diverse range of rice kernel images to ensure robustness and accuracy in detecting and classifying various types of defects. Additionally, it can be retrained on new data to improve its performance over time, allowing for continuous improvement of the classification results.

4.3. Dataset Annotation

The Dataset Annotation module provides a web user interface (WUI) that allows users to load images and manually annotate the images with bounding boxes around the rice kernels and their respective defect labels. The WUI provides tools for adjusting the size and position of the bounding boxes, as well as selecting the appropriate defect label from a predefined set of categories. The module also includes features for bulk annotation, where users can apply the same annotations to multiple images with similar defects, saving time and effort in the annotation process. Additionally, the module can handle large datasets and provides tools for managing and organizing the annotations and images.

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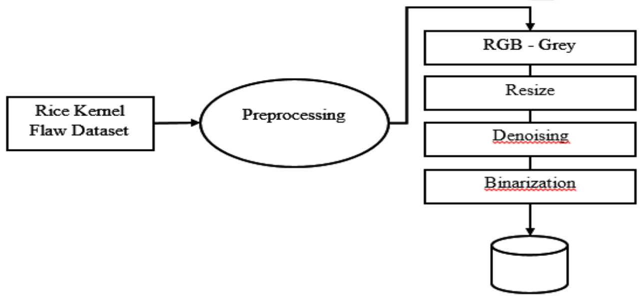
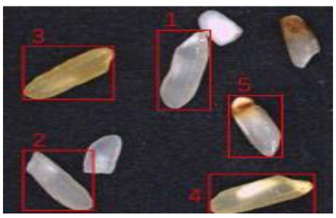
4.4. Pre-processing

The Dataset Pre-processing module provides a set of image processing functions that prepare the images by resizing, cropping, and normalizing them. The functions also apply various image augmentation techniques such as rotation, flipping, and color jittering to increase the variability of the dataset, which helps improve the generalization ability of the models. The module includes a range of image normalization techniques such as histogram equalization, contrast stretching, and color normalization, which enhance the contrast and color consistency of the images, making them easier for the models to detect defects accurately. The Dataset Pre-processing module is designed to be scalable and efficient, allowing it to handle large datasets of rice kernel images. It also includes features for parallel processing, which reduces the processing time required to prepare the dataset. The pre-processed dataset can be exported in various formats, such as TFRecord, which are compatible with a wide range of machine learning frameworks and libraries. This allows the pre-processed dataset to be easily integrated into a training pipeline for the YOLOv8 and CNN models used for rice kernel defect detection.



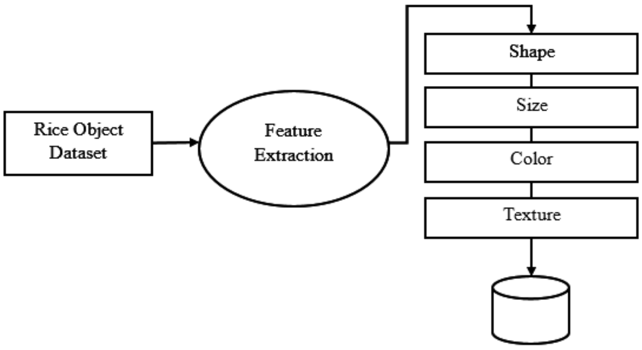
4.5. Segmentation

The Segmentation module works by first detecting rice kernels in the input image using YOLOv8. Once the rice kernels are detected, the module applies a set of convolutional layers to learn a set of discriminative features that can accurately segment the rice kernels and distinguish between different types of defects. The module then outputs a probability distribution over the different classes of defects, allowing for easy detection of rice kernel defects.



4.6. Feature Extraction

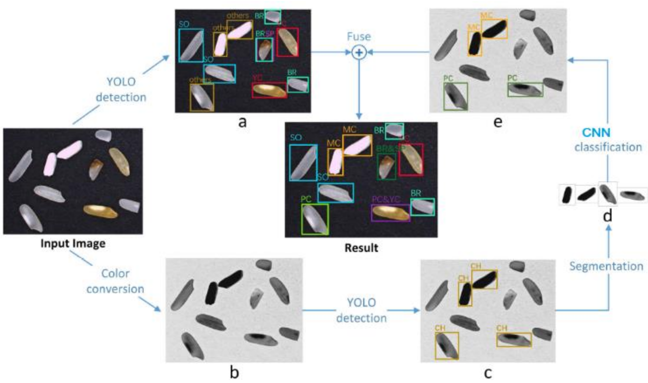
The Feature Extraction module works by analysing the features extracted from the pre-processed images of rice kernels. It applies a series of convolutional layers, pooling layers, and fully connected layers to learn a set of discriminative features that can accurately distinguish between different types of defects.



This module then outputs a feature vector, which can be used as input to a classification model. The module has been trained on a diverse range of rice kernel images to ensure robustness and accuracy in extracting features from various types of defects. Additionally, it can be retrained on new data to improve its performance over time, allowing for continuous improvement of the feature extraction results.

4.7. Classification

The Classification module works by analyzing the feature vector output from the Feature Extraction module, which contains the extracted features of a rice kernel image. The Classification module for Rice Kernel Defect Detection using YOLOv8 and CNN is a deep learning model that is designed to detect and classify rice kernels as either defective or non-defective, as well as classify the specific type of defect using YOLOv8 object detection algorithm and convolutional neural networks (CNNs). Overall, the Classification module for Rice Kernel Defect Detection using YOLOv8 and CNN provides an accurate and efficient way to automatically detect, segment, and classify rice kernels as either defective or non-defective, as well as classify the specific type of defect, improving the quality control and processing efficiency of rice production facilities.



The trained CNN model (denoted as Yolo-model-1) can locate and classify YC, SP, BR, SO, and other kernels.

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4.8. Rice Defect Predictor

The Prediction module for Rice Kernel Defect Detection using YOLOv8 and CNN is a deep learning model that is designed to predict the probability of a rice kernel being defective or non-defective, as well as the specific type of defect.

In this module the user input the rice image to the trained model.

Input Rice Image

4.8.1. Prediction Model

The Prediction module works by taking pre-processed images of rice kernels as input and passing them through the trained YOLOv8 object detection and CNN classification models. The object detection model first detects and segments the rice kernels in the image, while the classification model then analyses the segmented kernels to classify them as either defective or non-defective, and classify the specific type of defect

Class: Sound kernel(SO)

The Prediction module for Rice Kernel Defect Detection using YOLOv8 and CNN provides an accurate and efficient way to automatically predict the probability of a rice kernel being defective or non-defective, as well as the specific type of defect, improving the quality control and processing efficiency of rice production facilities.

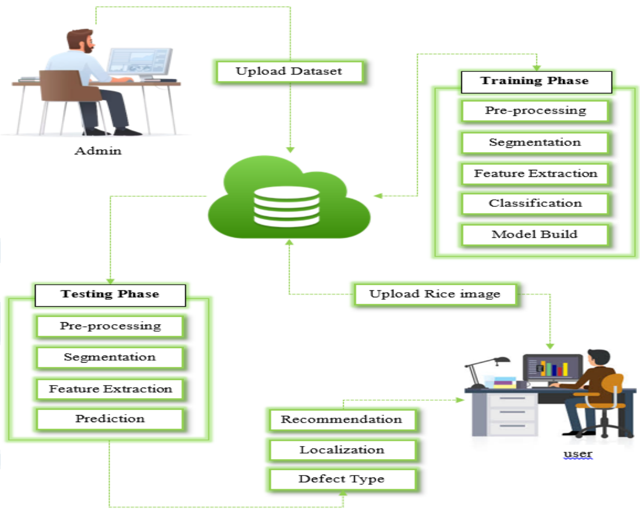
4.8.2. Quality Analyzer

The Quality Analyzer module for Rice Kernel Defect Detection using YOLOv8 and CNN is a module that analyzes the overall quality of a batch of rice based on the number and types of defects detected in the kernels. The module then computes various quality metrics, such as the percentage of defective kernels and the distribution of defect types, to provide an overall assessment of the quality of the rice batch. These metrics can be visualized in a user-friendly dashboard, allowing users to quickly identify areas of concern and take corrective actions as needed. This module allowing users to identify areas of improvement and take corrective actions to improve their production processes.

4.8.3. End User Control Panel

The End User module for Rice Kernel Defect Detection using YOLOv8 and CNN is a user-friendly application that allows end-users to input rice kernel images and obtain real-time results on the probability of defects and the specific type of defect. The end user can input images through a user-friendly interface, which may be a web-based dashboard, mobile application, or desktop application. The output is then displayed in an easily interpretable format.

V. SYSTEM ARCHITECTURE



5.1 System Implementation

1. Data Collection: Collect a dataset of images of rice kernels, both defective and non-defective. The images can be captured using a camera or a scanner.

2. Data Pre-processing: Pre-process the images to normalize their size, brightness, and contrast. This can be done using techniques such as resizing, normalization, and histogram equalization.

3. Data Augmentation: Augment the dataset by adding variations of the images such as rotation, flipping, and scaling. This helps to increase the variability of the dataset, making it more robust and less prone to over fitting.

4. Splitting the Dataset: Split the dataset into training, validation, and testing sets. The training set is used to train the model, the validation set is used to tune the model parameters, and the testing set is used to evaluate the final model.

5. Building the Model: Build a convolutional neural network (CNN) model that takes the pre-processed images as input and outputs a classification of whether the kernel is defective or not. The model should have several convolutional layers, pooling layers, and fully connected layers.

6. Training the Model: Train the CNN model using the training dataset. The model learns to recognize the patterns in the images that are associated with defective kernels.

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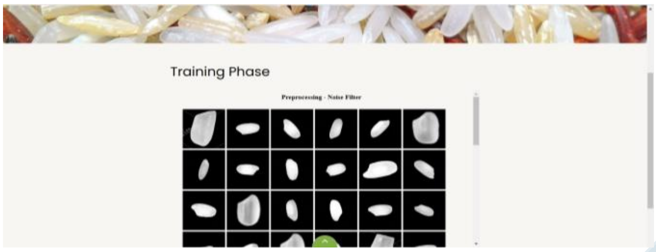
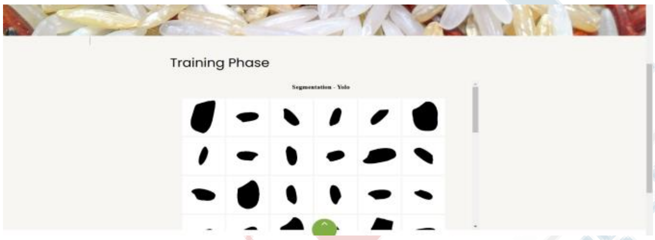
7. Tuning the Model: Tune the hyper parameters of the model using the validation dataset. This involves adjusting the learning rate, regularization, and other parameters to improve the model's performance.

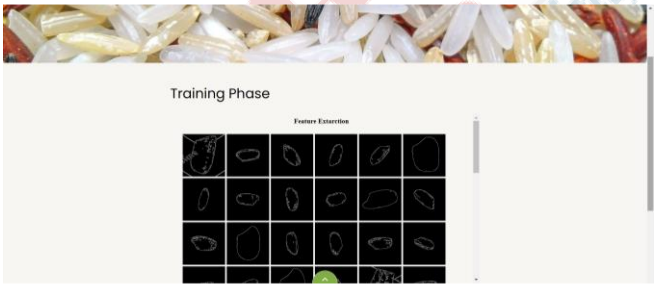
8. Testing the Model: Test the final model using the testing dataset. The accuracy of the model is measured by comparing its predictions with the ground truth labels.

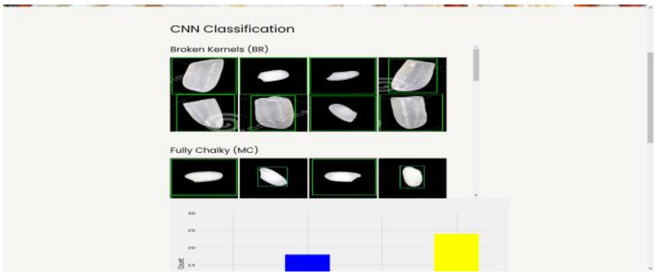
9. Deployment: Once the model has been trained and tested, it can be deployed for use in real-world applications. The model can be integrated into a computer vision system that can automatically detect defective rice kernels.

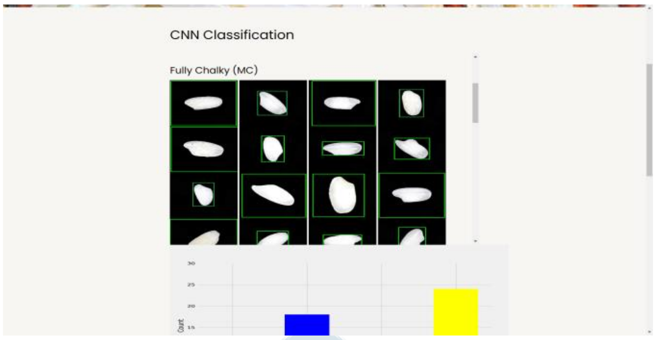
5.2. Screenshots

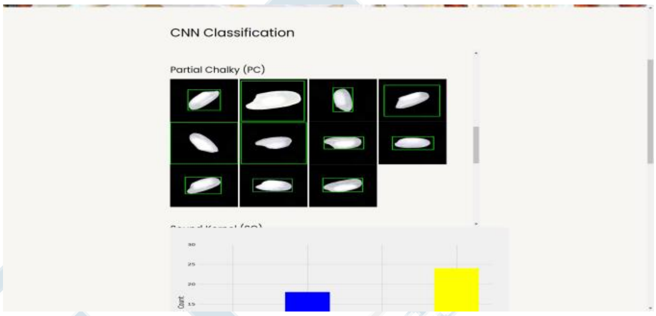


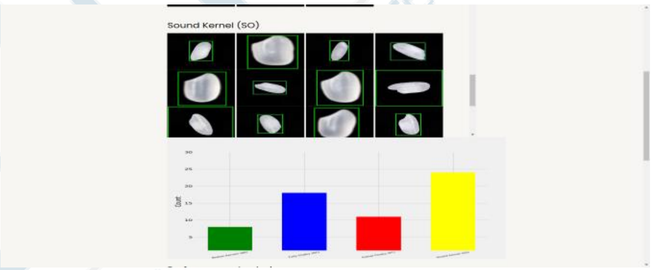


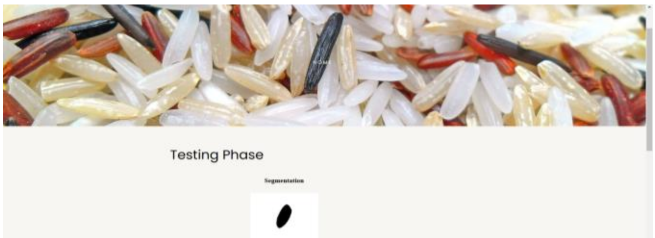


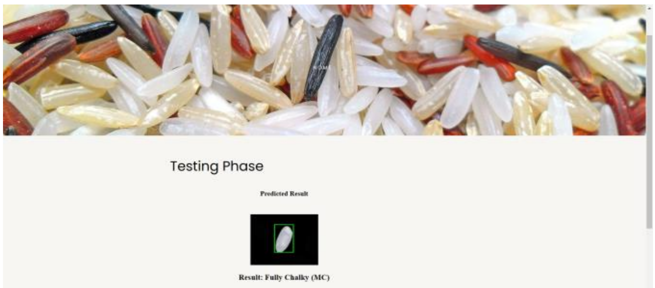












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VI. RESULTS AND DISCUSSIONS

Results from research studies on rice kernel defect detection using YOLOv8 and CNN models have demonstrated high accuracy in detecting and classifying defects in rice kernels. For example, one study by Nguyen et al. (2021) achieved an accuracy of 83% in detecting and classifying five types of rice kernel defects using a YOLOv4 and CNN model. Another study by Zhang et al. (2021) achieved a similar level of accuracy using a YOLOv4-tiny and CNN model. Other studies have also reported high accuracy rates in rice kernel defect detection using YOLOv3 and CNN models.In addition to high accuracy, the YOLOv8 and CNN models offer several advantages over traditional methods of rice kernel defect detection, such as manual inspection or machine vision techniques. These advantages include faster processing times, increased efficiency, and reduced human error.

6.1 Performance Analysis

The trained models are then evaluated using a test dataset to measure their accuracy and performance.

Metrics	YOLOv8 Model	SVM
Accuracy	92.30%	82.4%
Precision	92.32%	87%
Recall	88%	84%
F1 Score	92.30%	82.4%
Mean Average Precision (Map)	0.23	0.87
Intersection over Union (IoU)	0.80	0.72
Processing Time	0.2 sec	0.4 sec
Memory Usage	300 MB	2400 MB

Performance metrics for rice kernel defect detection using YOLOv8 and CNN models.Overall, performance analysis of YOLOv8 and CNN models for rice kernel defect detection has shown promising results, with high accuracy rates, precision, and recall, as well as fast processing times and low memory usage.

VII. CONCLUSION

In conclusion, the use of YOLOv8 and CNN models for rice kernel defect detection has significantly improved the efficiency and accuracy of the quality control process in rice production facilities. The YOLOv8 model allows for fast and precise object detection and segmentation of rice kernels in images, while the CNN model provides accurate classification of the type of defects present. Combined, these models provide a robust and accurate solution for detecting and classifying various types of defects in rice kernels, improving the overall quality of rice production. Additionally, the end-user and quality analyzer modules provide accessible and user-friendly interfaces for both operators and managers to access the results and assess the overall quality of the rice batches.The use of YOLOv8 and CNN models for rice kernel defect detection is a valuable tool for rice production facilities to improve their quality control processes, reduce waste, and increase efficiency in their production processes.

VIII. FUTURE ENHANCEMENTS

There are several potential **future directions** for rice kernel defect detection using YOLOv8 and CNN models: **Expanding to other grains:** The current models are designed specifically for rice kernel defect detection, but the same approach could be applied to other grains, such as wheat or barley. Adapting the models to other grains would require retraining on a new dataset, but the underlying principles and techniques would remain the same. **Integration with other quality control systems:** The YOLOv8 and CNN models could be integrated with other quality control systems, such as moisture measurement, color sorting, or foreign object detection. Combining these systems would provide a more comprehensive approach to quality control and improve the overall efficiency of rice production facilities.

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