

Assessing corn quality classification with deep-learning module

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ABSTRACT

This study presents a new classification framework for corn quality assessment using the you only look once version 8 (YOLOv8) deep learning architecture. Traditional corn-sorting methods are labor-intensive, time-consuming, and prone to human error. To address these challenges, this study proposes the corn quality classification (CQC) algorithm, an artificial intelligence (AI)-driven approach for automatically recognizing and categorizing pest- and disease-related defects. The proposed model uses YOLOv8, which integrates a convolutional neural network (CNN) backbone for feature extraction and object detection. The system was trained on labelled corn images to classify them into three categories: healthy, water rot, and bug. The model achieved an overall classification accuracy of 92.7%, with class-specific accuracies of 88.9% for healthy, 70% for water rot, and 100% for bug. Key performance metrics included a recall of 93%, an F1-score of 62%, a mean average precision (mAP) of 92.7%, and an intersection over union (IoU) of 52.3%. Additionally, the F1-confidence and recall-confidence curves provided further insights into the model's performance. The proposed classification framework and CQC algorithm demonstrate the feasibility of AI-powered agricultural monitoring systems, offering a reliable and efficient approach to corn quality assessment. By enabling consistent and accurate classification, the proposed system has the potential to reduce labor requirements and support precision agriculture practices for improved crop quality management.

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1. INTRODUCTION

Artificial intelligence (AI) has attracted increasing attention in agriculture because of its potential to improve crop monitoring, disease detection, and quality assessment. Corn, as one of the world's major staple crops, is an important target for AI-based detection and classification systems [1]. Remote sensing technologies, including satellite imagery and unmanned aerial vehicles (UAVs), have been combined with AI algorithms to obtain useful information from corn fields. Convolutional neural networks (CNNs) have demonstrated strong performance in analyzing high-resolution images for crop identification and mapping [2]–[4]. Image processing and computer vision techniques have also been applied to field images to extract relevant characteristics, such as leaf patterns, plant height, and visible disease symptoms [5]. In addition, the you only look once (YOLO) framework [6] has enabled real-time detection of corn seedlings

under field conditions [7], while feature-threshold and backpropagation neural-network methods have been proposed to identify impurities and breakage in harvested corn grains [8].

Accurate identification of pest- and disease-related defects is essential for evaluating corn quality. Machine learning (ML) techniques, particularly CNNs [9], together with YOLO-based models and OpenCV [10], provide effective tools for extracting visual features and recognizing quality-related patterns. CNN architectures have been widely used in various computer vision applications because of their ability to learn discriminative features directly from image data [11]–[13]. This capability makes them suitable for detecting and classifying defects that affect corn quality [14]. YOLO is especially attractive because it combines object localization and classification within a single network, supporting rapid image processing and real-time implementation [15]. Its suitability for agricultural applications has been demonstrated by several studies. Lemon-YOLO, for example, introduced an SE_ResGNet34 backbone and SE_ResNet modules, achieving 96.28% detection accuracy at 106 frames per second and outperforming several established object-detection models [16]. Des-YOLOv4 incorporated average precision (AP)-loss and soft-non-maximum suppression (NMS) to address class imbalance and overlapping apples, achieving a mean average precision (mAP) of 97.13%, a recall of 90%, and a processing speed of 51 frames per second [17]. Similarly, an improved lightweight YOLOv5s model increased maize detection accuracy from 93.2% to 96.3% and weed detection accuracy from 85.6% to 88.9% through data augmentation, SENet, and C3-Ghost-bottleneck modules [18].

Other object-detection architectures, including region-based convolutional neural network (R-CNN) [19], fast R-CNN [20], faster R-CNN [21], and mask R-CNN [22] have also contributed to agricultural image analysis by improving region proposal, feature extraction, object localization, and classification. The use of residual network (ResNet) and visual geometry group network (VGGNet) backbones has further enhanced maize tassel detection from UAV and mobile-phone imagery [23]. Improvements to YOLOv5-based networks have likewise demonstrated the potential to increase detection accuracy while maintaining computational efficiency [24]. These advances have been built upon the success of deep CNNs for large-scale image recognition, which established the foundation for many modern computer vision models [25]. However, despite these advances, comparatively limited attention has been given to the automated classification of harvested corn according to visible pest- and disease-related quality conditions. Table 1 therefore compares relevant studies in terms of their objectives, hardware and software configurations, algorithms, and reported accuracy. Table 1 highlights reliable approaches for crop monitoring and quality assessment. However, corn detection and grading still lack precise, efficient, and standardized automated methods. Manual inspection is labor-intensive, time-consuming, and subjective, which may reduce assessment accuracy, delay defect identification, and affect farmers' ability to manage and market their produce effectively. To address these limitations, this study makes the following contributions:

- i) A new classification framework: a CNN-based YOLOv8 framework is proposed to identify and classify corn quality defects caused by pests and diseases.
- ii) New corn defect classification results: the system distinguishes three corn quality classes and evaluates YOLOv8 performance in terms of classification accuracy.

Table 1. Comparison with previous studies

Reference	Objective	Hardware/software (algorithm)	Accuracy
[17]	Real-time apple detection for harvesting robots	MATLAB preprocessing and annotation (Des-YOLOv4)	– mAP = 97.13% – Recall = 90%
[16]	Efficient object detection method for lemons in natural environment	Intel Core i3-8100 CPU, NVIDIA Tesla V100 GPU (L-YOLO)	– 96.28%
[23]	Detection of maize tassels from UAV RGB imagery	UAV DJI Inspire 2 with ZENMUSE X5S camera, mobile phone (faster R-CNN with ResNet and VGGNet)	– 94.99% for UAV images – 95.95% for phone images
[5]	Corn seed identification based on shape and color features	Artificial neural network (ANN)	– 89% (BIMA-20 good vs bad) – 97% (BIMA-20 good vs NASA-29 good)
This work	Corn quality classification (CQC) based on pest- and disease-related defects	GF63 Intel(R) (CNN and YOLOv8)	– 92.7% overall accuracy – 88.9% for "healthy" – 70% for "water rot" – 100% for "bug"

2. PROPOSED FRAMEWORK

The proposed framework for classifying corn quality consists of three modules: i) data collection and preprocessing, ii) development of the CQC algorithm, and iii) postprocessing. In general, the core components of this framework are illustrated as phase 1 (data collection and preprocessing) and phase 2

(development of CQC algorithm). This framework serves as a comprehensive guide to address the main research question: how accurately can the proposed deep learning-based algorithm classify corn quality conditions? Figure 1 demonstrates the flowchart of the proposed classification framework.

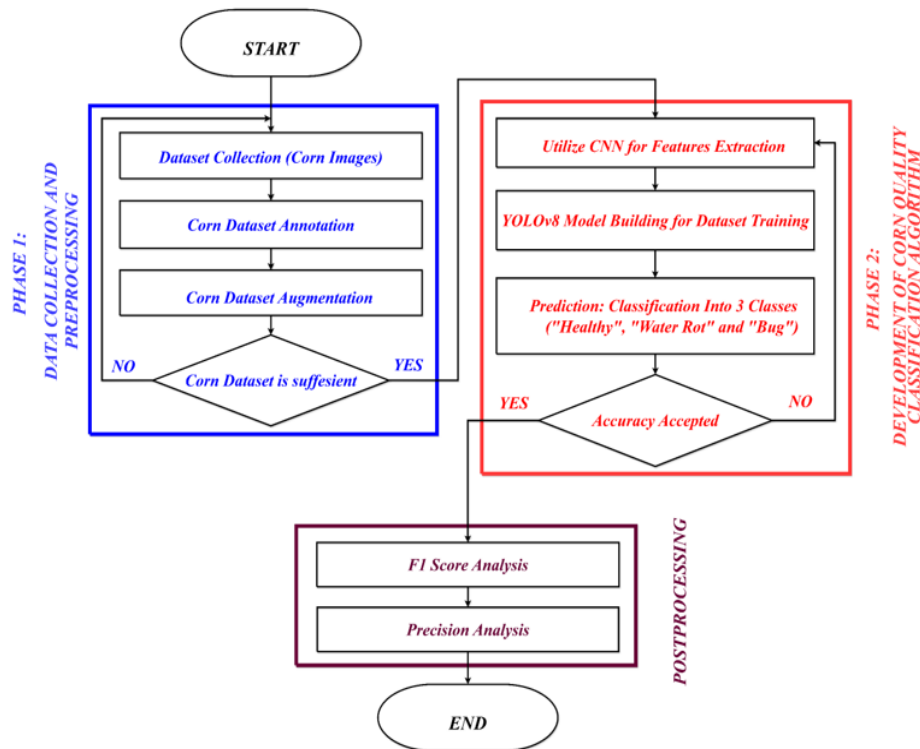


Figure 1. Flowchart of the proposed classification framework

2.1. Phase 1: data collection and preprocessing

The dataset consists of 771 farm images captured using a mobile phone from angled, overhead, and ground-level perspectives. These images reflect real corn-growing conditions rather than controlled or online sources. Figure 2 presents representative examples from the original farm-acquired dataset and illustrates the visual appearance of corn samples under natural acquisition conditions, including variations in color, texture, surface condition, and visible deterioration. Figure 2(a) shows a healthy corn sample with a normal visual appearance, whereas Figure 2(b) shows a spoiled corn sample exhibiting visible quality deterioration. These representative images illustrate the visual characteristics considered during the subsequent annotation of the dataset into the healthy, water rot, and bug classes.



Figure 2. Examples of corn images (a) healthy corn and (b) spoiled corn

The corn images were annotated into three classes: healthy, water rot, and bug. Rotation, flipping, and scaling were applied to increase data diversity and reduce overfitting, expanding the dataset to 1,771 images using the Roboflow application. The augmented dataset provided greater visual diversity, helping to reduce overfitting and improve the model's generalization to unseen images. The final dataset was divided into training, validation, and testing subsets of 85%, 8%, and 7%, respectively.

2.2. Phase 2: development of corn quality classification algorithm

A YOLOv8-based deep learning model was developed for automated CQC. The architecture uses a CNN backbone to extract visual features, followed by detection and classification heads for real-time object identification and categorization. YOLOv8 was selected for its accuracy, computational efficiency, and suitability for real-time applications. The model was trained using labelled maize images from three classes: healthy, water rot, and bug. The main steps used to develop the CQC algorithm are described as follows.

Algorithm 1. CQC algorithm

- i) Installation of dependencies and implementation using Python libraries: the required Python libraries were installed to set up the training environment. Several well-known Python libraries were used for model implementation:
 - TensorFlow: an open-source ML framework developed by Google, used for model development and training.
 - OpenCV: a computer vision library utilized for image preprocessing and augmentation.
 - NumPy: a numerical computation library used for handling image data and performing mathematical calculations.
- ii) Importing YOLOv8: the necessary modules were imported, and a YOLO-specific command was executed to verify the configuration.
- iii) Dataset integration: the custom dataset from Roboflow was loaded into the YOLOv8 format.
- iv) Model training and validation: the model was trained and evaluated using performance metrics such as precision, recall, and mAP.
- v) Inference and testing: the trained model was tested on unseen images to assess its real-world accuracy.

2.3. Postprocessing

To evaluate the performance of the corn classification algorithm, PyCharm, an integrated development environment (IDE), was used, and several key evaluation metrics were analyzed. These metrics include intersection over union (IoU), precision, recall, F1-score, AP, and mAP. The mathematical expressions for these metrics are provided in (1) to (6).

$$IoU = \frac{\text{area of over image}}{\text{area of union image}} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\text{-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (4)$$

$$AP = \int_0^1 P(r)dr \quad (5)$$

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (6)$$

3. RESULTS AND DISCUSSION

This study evaluates the performance of the CQC algorithm described in subsection 2.2 using the F1-confidence curve shown in Figure 3. The F1-score represents the balance between precision and recall. The healthy class maintained the highest F1-score across most confidence thresholds, indicating consistent classification performance, while the bug and water rot classes achieved lower scores and were more sensitive to threshold changes. The best overall performance was obtained at a confidence threshold of 0.287, where the combined F1-score reached 0.62, representing the most balanced trade-off between precision and recall across all classes.

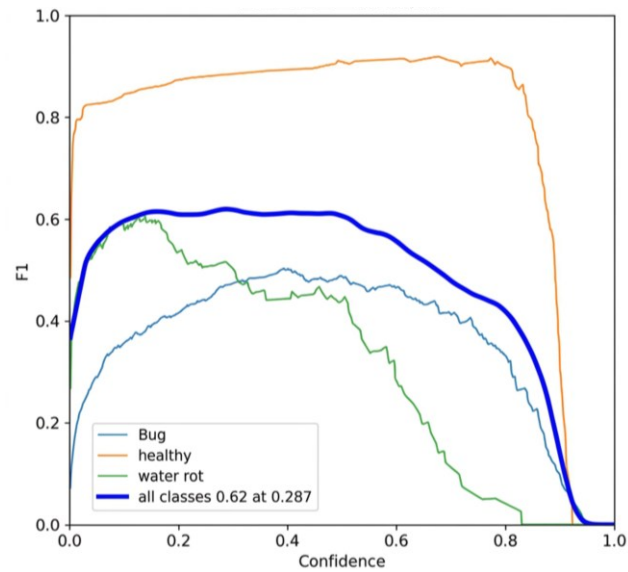


Figure 3. F1-confidence curve for the three corn classes

As shown in Figure 4, the healthy class maintained consistently high recall across most confidence thresholds, indicating reliable detection performance. In contrast, the recall values for the bug and water rot classes gradually decreased as the confidence threshold increased, showing greater sensitivity to threshold selection. The model achieved an overall recall of 0.93 at a confidence threshold of 0.000, indicating maximum sensitivity at the lowest threshold. However, selecting an appropriate threshold remains important to balance recall with prediction reliability.

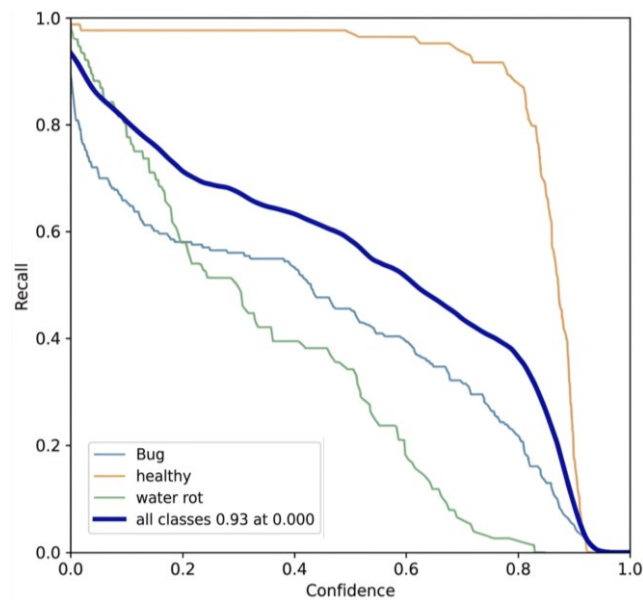


Figure 4. Recall-confidence curve for the three corn classes

As shown in Figure 5, the model achieved an overall precision of 1.00 at a confidence threshold of 0.924. The healthy class maintained relatively high precision across most thresholds, indicating more consistent predictions. In contrast, the bug and water rot classes showed greater variation, suggesting that their prediction reliability was more sensitive to the selected confidence threshold. Although precision increased at higher thresholds, this should be considered together with recall to determine a suitable operating point.

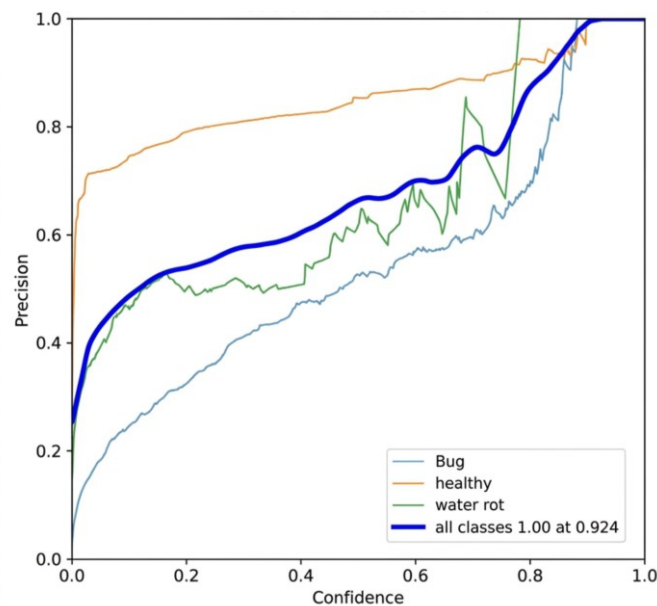


Figure 5. Precision-confidence curve

The proposed CQC algorithm was evaluated using a dedicated test subset comprising 124 images, representing 7% of the total dataset of 1,771 images. These images were excluded from training and validation to provide an independent assessment of model performance. The test dataset consisted of three classes: healthy (54 images), bug (60 images), and water rot (10 images). The trained YOLOv8 model was applied to these unseen images, and predictions were compared against the ground truth labels to assess classification performance. Figure 6 presents the raw and normalized confusion matrices, respectively, providing a comprehensive evaluation of the classifier's performance across the three classes. These matrices highlight the model's strengths and weaknesses by showing both the number and proportion of correct and incorrect classifications. As shown in Figure 6(a), the confusion matrix demonstrates strong classification performance across the three corn categories. All 60 bug samples were correctly classified, indicating that the model effectively recognizes insect-related damage. For the healthy class, 48 of 54 samples were correctly identified, while 4 were misclassified as bug and 2 as water rot. The water rot class achieved 7 correct predictions out of 10, with 2 samples misclassified as healthy and 1 as bug. This lower performance may be attributed to the limited number of water rot samples and the visual similarity between early-stage water rot and healthy corn. The normalized confusion matrix in Figure 6(b) confirms class-specific accuracies of 100% for bug, 88.9% for healthy, and 70% for water rot. Overall, the proposed CQC algorithm performed reliably for bug and healthy corn, although further improvement is needed for the water rot class through increased data representation and enhanced feature learning. The overall test accuracy of 92.7% demonstrates the effectiveness of the proposed deep learning framework.

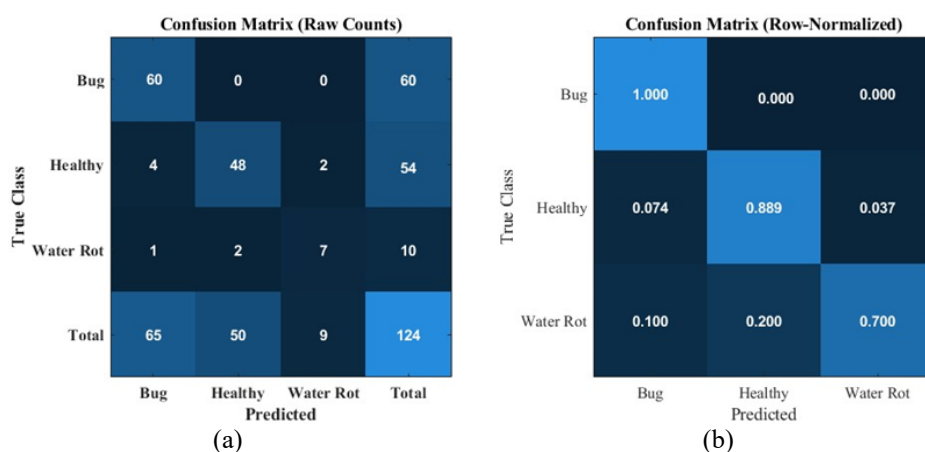


Figure 6. Confusion matrices (a) raw counts and (b) row-normalized values

The overall test accuracy of 92.7% demonstrates competitive performance for the proposed three-class corn-quality task. Previous agricultural vision studies reported 96.28% detection accuracy for Lemon-YOLO [16], 97.13% mAP for apple detection using Des-YOLOv4 [17], and improved maize detection accuracy of 96.3% using an enhanced YOLOv5 model [18]. Faster R-CNN has also achieved 94.99% and 95.95% detection performance for maize tassels acquired from UAV and mobile-phone imagery, respectively [23]. However, these numerical values should not be interpreted as direct rankings because the studies employ different datasets, target objects, class definitions, evaluation metrics, and acquisition conditions. The present study instead addresses the distinct problem of differentiating healthy corn from pest- and disease-related quality deterioration using farm-acquired imagery.

4. CONCLUSION

This study demonstrates the effectiveness of the proposed CQC algorithm, achieving an overall accuracy of 92.7%. The model attained class-specific accuracies of 100% for bug, 88.9% for healthy, and 70% for water rot. The lower performance for water rot was mainly associated with the limited number of annotated samples, which caused class imbalance and reduced the model's ability to generalize. The model also achieved 93% recall, a 62% F1-score, 92.7% mAP, and 52.3% IoU. These findings address the research question by confirming that the proposed deep learning approach can provide reliable and efficient automated corn quality assessment. Future work should expand and balance the dataset, improve performance for visually challenging samples, and integrate the system into precision agriculture applications for large-scale deployment.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest. Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Roboflow at <https://share.google/ZdidNEn1T0Jt9Tnzg>.

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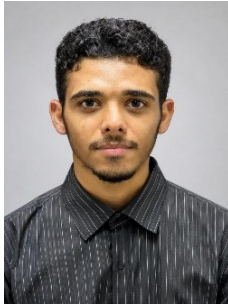
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