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IMAGE-BASED CANOLA SEED DETECTION AND COUNTING USING YOLOV8N AND YOLO11N OBJECT DETECTION MODELS

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Abstract
Accurate seed counting is a key component in seed quality assessment, breeding programs, germination and crop productivity analysis, and counting canola (Brassica napus L.) seeds is essential. The traditional methods of seed counting are time-consuming, labor-intensive, and subject to human errors, particularly in the processing of large quantities of samples. The development of computer vision and deep learning techniques has been seen as a very promising approach to the automated recognition and counting of objects in agriculture in recent years. This paper proposes an image-based automatic canola seed detection and counting method based on YOLOv8n model and YOLO11n models. A customized dataset of 833 images of canola seeds in natural light was created. The images in the dataset comprised different numbers of seeds (from one to ten). Each image was annotated by hand in the Computer Vision Annotation Tool (CVAT) with only one class, "canola_seed". The dataset was split into 666 train images and 167 validation images. Both YOLOv8n and YOLO11n models were trained for 50 epochs and evaluated using F1-score, mean average precision (mAP@50), and confusion matrix analysis. The results on the experimental set indicate that the YOLOv8n model had a mAP@50 of 0.965 and an optimal F1 score of 0.95, and the YOLO11n model had a mAP@50 of 0.969 and an optimal F1 score of 0.97. YOLOv8n and YOLO11n had mAP@50-95 of 0.270 and 0.266, respectively. Moreover, YOLO11n had fewer false-positive and false-negative results compared with YOLOv8n, demonstrating the reliability of the detection and counting process. The results show that YOLO11n was superior to automated canola seed detection and counting. The proposed framework is a solution that can be used for seed quality testing, agricultural phenotyping, and future smart agriculture applications, which is low-cost, accurate, and efficient.

INTRODUCTION

Assessment and evaluation of canola (Brassica napus L.) seed-related traits is critical for crop breeding, seed quality testing, germination studies, and yield analysis, considering the importance of the crop to the economy. One of these traits is seed counting, which offers information about seed quality, seed yield performance, and agricultural research activities. [1], [2].

Seeding count has been traditionally done by the labor-intensive method of the laboratory technician and researchers. Manual counting is easy and cheap but time-consuming, labor-intensive, and prone to human error, particularly if a large number of seed samples need to be processed. The need for high-throughput phenotyping and precision agriculture is a growing need, and automation of the image-based solution is increasingly important to lower the labor requirements and improve detection performance [3], [4].

The development of computer vision and deep learning has revolutionized agricultural monitoring and crop phenotyping. Digital images of agricultural objects can be automatically identified, localized, and counted by deep learning-based object detection models to achieve an F1-score of 90%. They have been successfully used in several agricultural applications such as wheat ear counting, wheat seed detection, rice seed germination analysis, soybean pod counting, fruit counting, and plant stand estimation [5-9]. Compared with traditional image processing techniques, deep learning methods can learn complex visual features directly from image data and provide robust performance under various environmental conditions.

Deep learning methods have the advantage of being able to learn complex visual features directly from image data and yield high performance across a range of environments, compared to traditional image processing techniques. There are several studies regarding the use of deep learning in canola and rapeseed research. UAV image analysis has been applied to the counting of flowers [10] and estimating the stand number [11] in rapeseed, as well as flower phenotyping [12] and biomass prediction [13] and pod segmentation [14] and detection of sedges. For instance, Li et al. suggested a deep learning method to count rapeseed flowers automatically from UAV RGB images and tested the performance of object detection techniques in crop monitoring [10]. Likewise, Zhang et al. estimated the number of rapeseed stands using UAV imagery and CNN and obtained good detection results for rapeseed plants [11]. In the past, other scholars have used the methods YOLOv8, masked R-CNN, and point cloud segmentation to analyze rapeseed pods and sedges [13], [14]. While such studies have helped to further the phenotyping of rapeseed, the majority of them have concentrated on the plant surface or pod surface traits rather than seed detection and counting. There has also been much interest in automatic seed counting in the last few years. SeedQuant was designed to be a deep learning automated seed identification and counting tool [3]. In parallel, a few research works have been conducted on the detection of wheat seeds, monitoring of rice seed germination, and seed counting in the laboratory using YOLO architectures [5], [6]. The following observations were made during these studies: Deep learning models can be successfully applied to detect very small seed objects even in the face of challenges including the presence of overlap, light variation, and background complexity. To date, most studies on seed number counting have been conducted on wheat, rice, and other crop species, and only a few studies have been conducted on canola seed detection in advanced YOLO architectures. YOLO family has emerged as the most popular framework of object detection algorithms, as it offers a balance between the recognition F1-score and computational efficiency. YOLO-based models have been demonstrated to be effective in different agricultural counting tasks like soybean pod counting, wheat ear detection, and crop phenotyping [7], [8], [15]. The recently developed YOLOv11 provides improved robustness and enhances performance on small objects, and YOLOv8 has enhanced feature extraction and localization. But the performance of YOLOv8n and YOLOv11n in detecting and counting canola seeds has not been well explored.

To fill this research gap, this study proposes an image-based canola seed detection and counting framework based on the two object detection models: YOLOv8n and YOLOv11n. A custom dataset of 833 images of canola seeds under natural sunlight was created. Images were manually annotated with the Computer Vision Annotation Tool (CVAT), and images contained different seed combinations ranging from one to ten seeds per image. The same datasets and experimental settings were used for training and validation/evaluation of both models. They have been assessed by means of an F1-score, mean average precision (mAP@50), and a confusion matrix analysis.

The major findings of this study can be summarized as follows:

1. A custom image dataset consisting of 833 canola seed images under natural sunlight conditions was generated.
2. CVAT was used for manual annotation, using only one object class, "canola_seed."
3. YOLOv8n and YOLO11n models were developed and tested to detect and count canola seeds.
4. A comprehensive performance evaluation was conducted using standard object detection metrics.
5. An efficient and low-cost framework for automated canola seed counting was developed to support agricultural phenotyping and seed quality assessment applications.

In the remainder of this paper, we present our findings. The literature review of related studies presented in Section 2 discusses the previous research conducted on agricultural commodity detection and seed counting. The dataset preparation, interpretation procedures, model architectures, and experimental setup are described in Section 3. The experimental results and comparison between YOLOv8n and YOLO11n are provided in Section 4. The last section, Section 5, summarizes this study and suggests future research.

1. RELATED WORK

The field of computer vision and deep learning has recently seen great progress in the area of automated object detection and counting that has enhanced the ability to count and identify objects in agricultural settings. Manual count techniques, which rely on personnel, can be tedious, time-consuming, and susceptible to errors entered by humans. Therefore, automated crop monitoring, phenotyping, and counting have become more and more the focus of research using deep learning approaches [3], [4]. Several studies have examined the image-based phenotyping and counting methods in rapeseed and canola research. The study [10] proposed a deep learning model for automatic rapeseed flower counting from RGB-based UAV images and showed the efficacy of flower counting with an object detection model. The study [11] applied convolutional neural networks and UAV imagery to estimate rapeseed stand counts during the leaf growth stages. Likewise, [16] developed an early growth stage (seedling stage) UAV-based stand counting and seed performance assessment (SPA) method for the rapeseed plant model. The use of aerial image analysis for the control of crops was indicated in these studies. Usually, they were not dealing with the detection of an individual seed but rather with physical characteristics of the plant surface. Research on the analysis of rapeseed pods and on the silique of rapeseed has been investigated further. The study [14] introduced a deep learning-based point cloud segmentation method for rapeseed siliques, while [13] used YOLOv8 and Mask R-CNN for rapeseed pod segmentation and phenotype calculation. The study [17] proposed a rapeseed flower counting framework based on GhP2-YOLO and StrongSORT algorithms. The study [18] came up with the idea of implementing a lightweight model called SPL-YOLOv8. Despite these studies showing the power of deep learning in phenotyping rapeseed, they did not aim at counting seeds. Research on canola has been primarily directed to crop identification and yield estimates. The study [2] used deep learning techniques for canola identification by deep learning techniques for precision weed management systems. The study [1] attempted to evaluate floral traits in canola using UAV imagery and correlate with seed yield. More recently, [19] presented an automatic phenotyping approach to oilseed rape plants based on time-series images. While these studies have helped advance the phenotyping of canola, the direct image-based counting and detection of canola seeds have yet to be extensively studied. Seed counting has been in the spotlight of increasing interest in recent years. The study [4] presented an automated seed counting system based on image processing and deep learning. The study [3] presented a deep learning-based tool called SeedQuant for estimating seed number and germination response. A framework that detects the objects in the images and measures the plant fitness traits was proposed in study [20] to achieve the aim of measuring the plant fitness traits with plant-seed counting. The studies proved that the deep learning algorithms can identify and count the seeds accurately. Their data, however, were primarily for Arabidopsis and other plants but not canola. These studies demonstrated that deep learning can accurately identify and count seeds. However, their datasets mainly included Arabidopsis and other plant species rather than canola. YOLO-based models have shown remarkable performance for seed detection and counting tasks. YOLOv8-HD was also proposed in the study [5] for wheat seed detection and counting, which achieves high accuracy under challenging conditions. There are studies like [6] that introduced RSG-YOLO for rice seed germination detection, and another study by Yao et al. introduced SGR-YOLO for wild rice seed germination analysis. The evaluation performed in these studies demonstrated that state-of-the-art YOLO-like neural networks can be applied to accurately identify tiny seed entities and could be capable of detecting overlapped instances. Object counting is also extensively studied in agricultural applications such as counting wheat ears. In the study [9], they introduced a robust method to detect wheat ears using the EfficientDet model with an optimized configuration. In the study [21], YOLOv7-MA was proposed for wheat head detection and counting under complex field conditions. More recent studies have improved the architectures of YOLOv10 and YOLOv11 for wheat ear counting and localization, which show robust performance in dense agricultural landscapes [22], [23]. Another area of related research is the soybean pod count. In the study [24], the depth camera was used along with the YOLOv7 architecture to detect and count the soybean pods automatically. In order to count soybeans from a high-resolution image, the study [8] suggested a podnet. SPCN is a density map-based soybean pod counting network presented in the study [7], while the study [15] presents the YOLOv8n-POD for soybean pod detection. With this research, it was shown that the small and densely distributed nature of agricultural objects can be effectively addressed by deep learning models for counting applications. While substantial advances have been achieved in crop counting, plant phenotyping, seed germination analysis, and pod detection, there remain significant gaps in research and development related to Automated Canola Seed Detection and Count. While most studies within the canola sector are based on flower analysis, biomass estimation, stand counting, and/or pod segmentation, there are usually few studies concerned with seed counting undertaken in wheat, rice, soybean, and Arabidopsis. Furthermore, comparative evaluations of YOLOv8n and YOLO11n for canola seed counting have not been extensively investigated. This study fills this gap by creating a custom canola seed dataset and identifying the test performance of YOLOv8n and YOLO11n for automated canola seed detection and counting from images.

2. MATERIALS AND METHODS

In this section, the various steps of data preparation, image interpretation, object detection models, and the experimental setup used in this study, and, finally, its evaluation metrics are explained. To assess the efficiency of automatic seed identification and counting, a custom canola seed image dataset was developed and tested. A custom-made image dataset of canola seeds was created to evaluate the efficiency of automatic seed identification and counting using models such as YOLOv8n and YOLO11n.

2.1 Collecting the dataset

A specially created image dataset for canola seed detection and counting was developed. 833 images were captured with a smartphone camera under natural sunlight conditions. During image acquisition, canola seeds were placed on a white background to minimize background complexity and improve object visibility. The images with varying numbers of seeds from 1 to 10 were sufficient for training and evaluating the models, as shown in Figure 1.

Figure 1. Sample images of canola seeds containing different seed counts used for dataset creation.

The image acquisition process was done by hand to ensure that the seeds were placed at various positions and orientations and at different spatial distributions. This variation was introduced to improve model generalization and robustness. The collected images represent real-world laboratory conditions and provide diverse examples for object detection tasks. Then, the collected images were manually annotated with CVAT to prepare them for object detection model training (Figure 2).

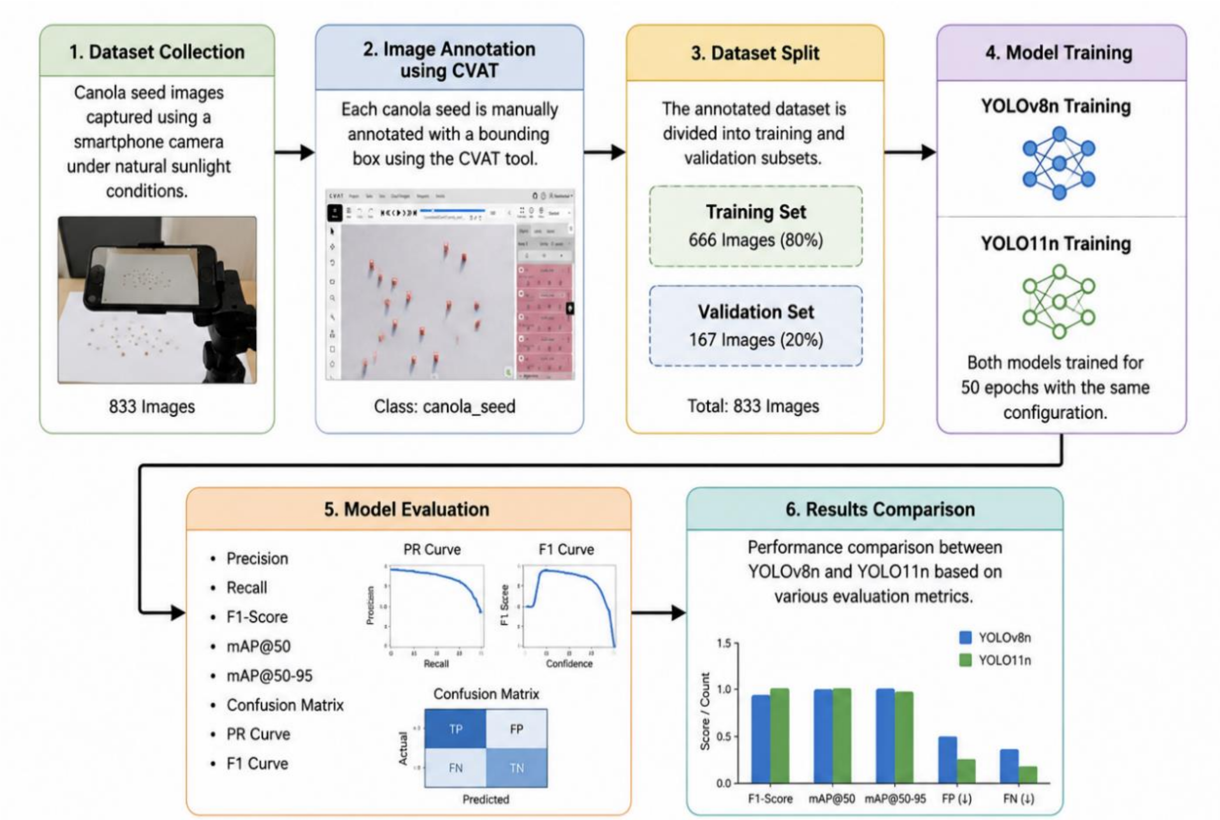

Figure 2. Overall workflow of the proposed canola seed detection and counting framework using YOLOv8n and YOLO11n.

The full dataset consisted of 833 images and was divided into training and validation subsets. A total of 666 images (80%) were used for model training, while 167 images (20%) were reserved for validation. Table 1 summarizes the distribution of the dataset.

Table 1. Dataset Distribution

Dataset Split	Images
Training	666
Validation	167
Total	833

The developed dataset serves as the basis for automatic canola seed detection and counting using deep learning models.

3.2 Image annotation using CVAT

The image annotation was carried out by means of the Computer Vision Annotation Tool (CVAT), which is commonly used for the preparation of object detection datasets. The bounding box around each canola seed was drawn by hand for each seed visible in the image. All instances of seeds were annotated using a single object class, "canola_seed," as shown in Figure 3.

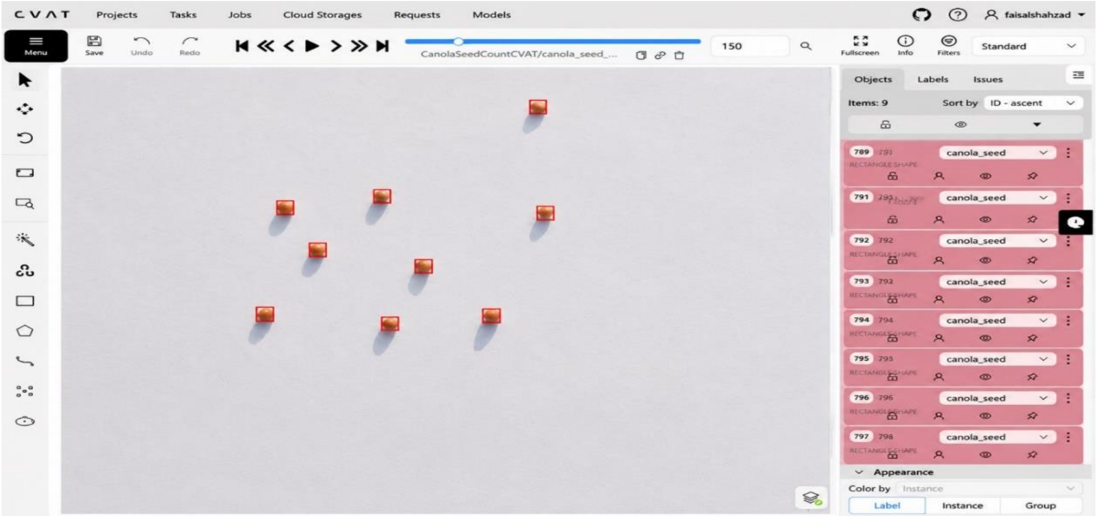

Figure 3. Annotation of canola seed images using the CVAT tool

The process of annotation consisted of carefully identifying the individual seeds by drawing boxes around them while trying to limit the inclusion of background. The dataset was uniformly annotated to guarantee the quality of annotations and minimize labeling errors. The dataset was then annotated and exported in the YOLO format, where the normalized object coordinates and the class identifiers are both compatible with the YOLO training framework.

The annotation process resulted in about 3824 labeled instances of seeds in the dataset. The annotations were acquired as ground truth information for supervised learning and model assessment.

3.3 YOLOv8n Architecture

YOLOv8n is a lightweight version of the YOLOv8 object detection family made by Ultralytics. The three main components of the architecture are the spine, the neck, and the detection head. The spine extracts hierarchical visual features from input images, and the neck fuses multi-scale visual features to achieve better object localization. Object classes and the coordinates of bounding boxes are predicted at various feature scales by the detection head.

YOLOv8 presents an anchor-free method for detection and an enhanced feature aggregation strategy to boost detection's F1 score with computational efficiency. YOLOv8n's smaller size allows it to be used in resource-limited environments or for small object detection.

YOLOv8n was trained with the self-built canola seed dataset, and the automatic recognition and counting accuracy of seeds were tested.

3.4 YOLO11n Architecture

The most recent YOLO version, YOLO11n, has the best feature extraction capacity and object localization and detection F1-score compared to the previous versions of YOLO. Just like any other architecture, the YOLO11n architecture comprises the backbone, feature fusion neck, and detection head components.

There have been changes in the architectural design that enhance feature extraction capacity as well as improve the accuracy of detection. This has been done by ensuring that the accuracy of detecting small objects even under the harshest visual conditions is quite robust.

The canola seeds are relatively small objects and have a low number of visual features. Due to this reason, it was deemed necessary to test the newest architecture together with YOLOv8n to assess the improvements in the detection and F1-score of canola seed counting.

3.5 Experimental setup

The experiments were conducted using the Google Colab cloud computing platform. Model training and evaluation were performed using the Ultralytics YOLO framework with GPU acceleration provided by Google Colab. Both YOLOv8n and YOLO11n models were trained under the same computational environment and training configuration to ensure a fair performance comparison.

All experiments were conducted using the same dataset, training sequence, and evaluation procedure to ensure a fair comparison between YOLOv8n and YOLO11n. The annotated dataset was divided into training and validation subsets containing 666 and 167 images, respectively.

Both models were trained for 50 epochs using the YOLO training framework. During training, images were automatically resized and processed using standard YOLO data augmentation techniques. Model performance was continuously monitored using validation data throughout the training process (Table 2).

The experiment aimed to compare the detection performance of YOLOv8n and YOLO11n for counting canola seeds under identical conditions. The best-performing model was selected based on detection F1 score, mAP values, and confusion matrix results.

Table 2. Training Configuration

Parameter	Value
Total Images	833
Training Images	666
Validation Images	167
Classes	1
Class Name	canola_seed
Epochs	50
Annotation Tool	CVAT
Detection Models	YOLOv8n, YOLO11n
Platform	Google Colab
Framework	Ultralytics YOLO

3.6 Evaluation Metrics

The performance of YOLOv8n and YOLO11n was evaluated using standard object detection metrics, including precision, recall, F1-score, mean average precision (mAP@50), and confusion matrix analysis.

Precision measures the proportion of correctly detected objects among all predicted objects and is defined as:

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

Where TP represents true positives, and FP represents false positives.

Recall measures the model's ability to correctly identify all target objects and is calculated as follows:

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

The F1-score provides a balanced measure of precision and recall and is calculated as follows:

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

The **mean average precision at IoU threshold 0.5 (mAP@50)** for primary object detection was used as the evaluation metric. This metric evaluates both the localization F1 score and object classification performance.

In addition, a confusion matrix was analyzed to determine the number of seeds correctly detected. These matrices collectively provide a comprehensive assessment of the model's performance for canola seed detection and counting.

3. RESULTS AND DISCUSSION

This section presents an evaluation of the performance of the YOLOv8n and YOLO11n object detection models on the custom canola seed dataset. Both models were trained using the same dataset, annotation strategy, and training sequence to ensure fair comparisons. The evaluation was performed using precision, F1-score, mAP@50, precision-recall curves, confidence curves, and confusion matrix analysis.

4.1 YOLOv8n Performance

The YOLOv8n model demonstrated strong detection capability for canola seed identification and counting. The training and validation curves indicated stable convergence throughout the training process, suggesting efficient feature learning and good model generalization.

The precision-confidence curve shows that the model achieved a precision value of approximately 1.00 at a confidence limit of 0.543. Similarly, the F1-Confidence curve indicated a maximum F1-score of 0.95 at a confidence limit of 0.264. These results indicate that YOLOv8n was able to achieve a good balance between precision and recall for canola seed detection.

The Precision-Recall curve produced an mAP@50 value of 0.965, indicating high object localization and classification performance. Furthermore, confusion matrix analysis revealed that the model correctly detected 844 seed events while generating 39 false positives and missing 20 seed samples (Table 3).

Table 3. YOLOv8n Detection Performance

Metric	Value
Best F1-Score	0.95
mAP@50	0.965
mAP@50-95	0.270
True Positives	844
False Positives	39
False Negatives	20

The performance of YOLOv8n was evaluated using precision, recall, F1-score, and mAP metrics. The training results and evaluation curves are presented in Figure 4.

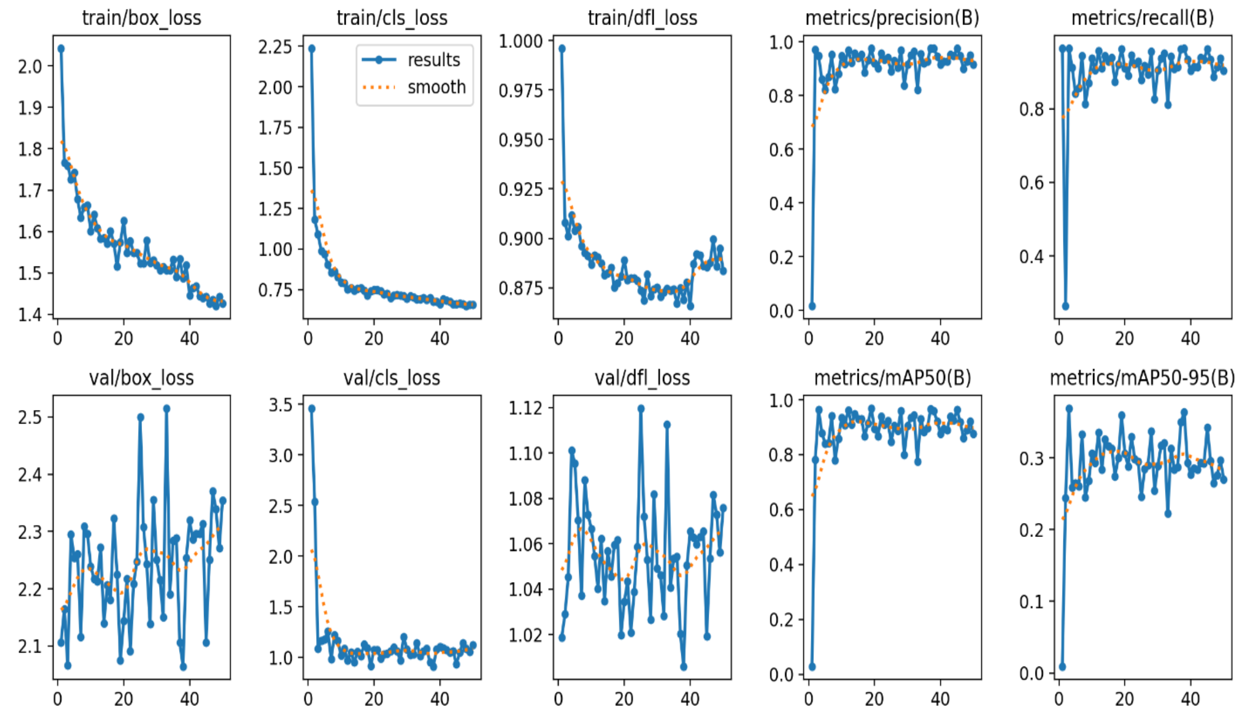

Figure 4. YOLOv8n Training Results

Figure 5 presents the evaluation results of the YOLOv8n model, including precision-recall curves, F1-confidence curves, and confusion matrix outputs.

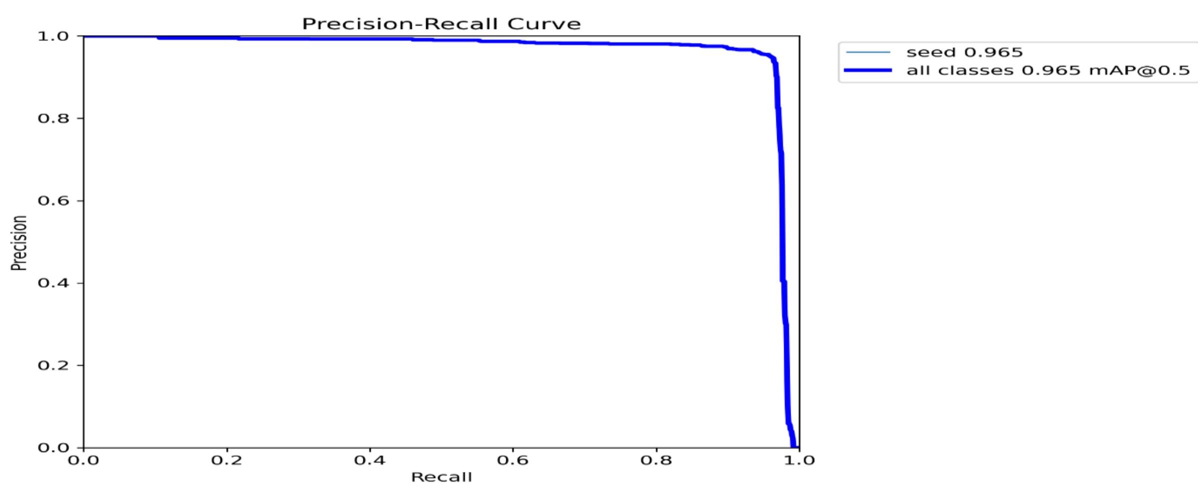

Figure 5. YOLOv8n Precision-Recall Curve

As shown in Figure 6, the YOLOv8n model correctly detected 844 seed instances while producing 39 false positive detections and 20 false negative detections. The confusion matrix demonstrates that the model achieved a high level of classification accuracy for the single canola seed class, although a small number of detection errors remained under certain image conditions.

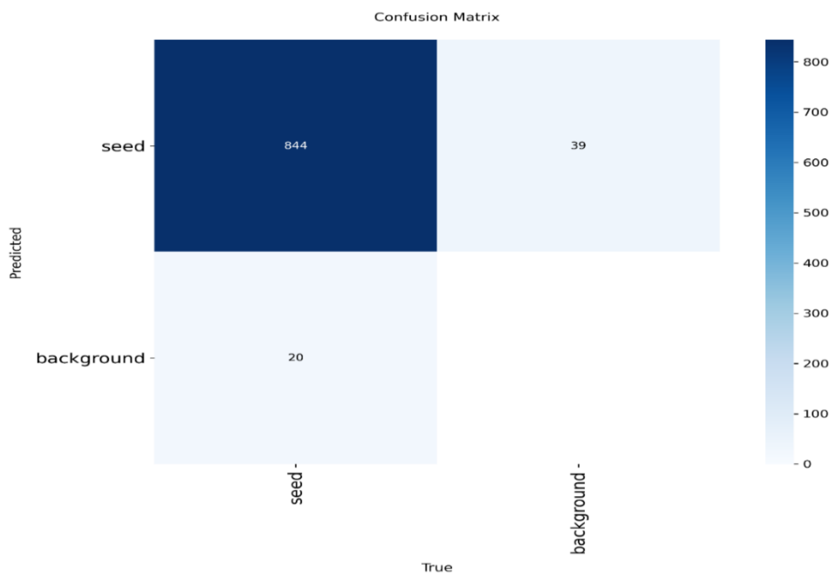

Figure 6. Confusion matrix of the YOLOv8n model on the canola seed validation dataset

The overall results show that YOLOv8n can effectively detect small canola seeds under natural lighting conditions. However, a small number of false detections and missed detections were observed, which can be attributed to variations in seed orientation, lighting conditions, and object appearance.

4.2 YOLO11n Performance

The YOLO11n model achieved superior performance compared to YOLOv8n in most of the evaluation metrics. The training curves showed stable convergence and continuous validation performance, indicating effective learning of canola seed characteristics.

The precision-confidence curve shows that YOLO11n achieved a precision value of 1.00 at a confidence limit of 0.828. The F1-Confidence curve reported the highest F1-score of 0.97 at a confidence limit of 0.585, which was higher than the score achieved by YOLOv8n.

The precision-recall curve produced an mAP@50 value of 0.969, demonstrating excellent detection performance. The confusion matrix shows that YOLO11n correctly detected 848 seeds while producing only 16 false positives and 16 false negatives. These results indicate improved localization accuracy and reduced detection errors (Table 4).

Table 4. YOLO11n Detection Performance

Metric	Value
Best F1-Score	0.97
mAP@50	0.969
mAP@50-95	0.266
True Positives	848
False Positives	16
False Negatives	16

Figure 7 illustrates the training and validation performance of the YOLO11n model across all epochs. The training curves indicate a continuous reduction in localization and classification losses, while precision, recall, and mAP values increased steadily. These results demonstrate that the model learned the seed features effectively without significant signs of overfitting.

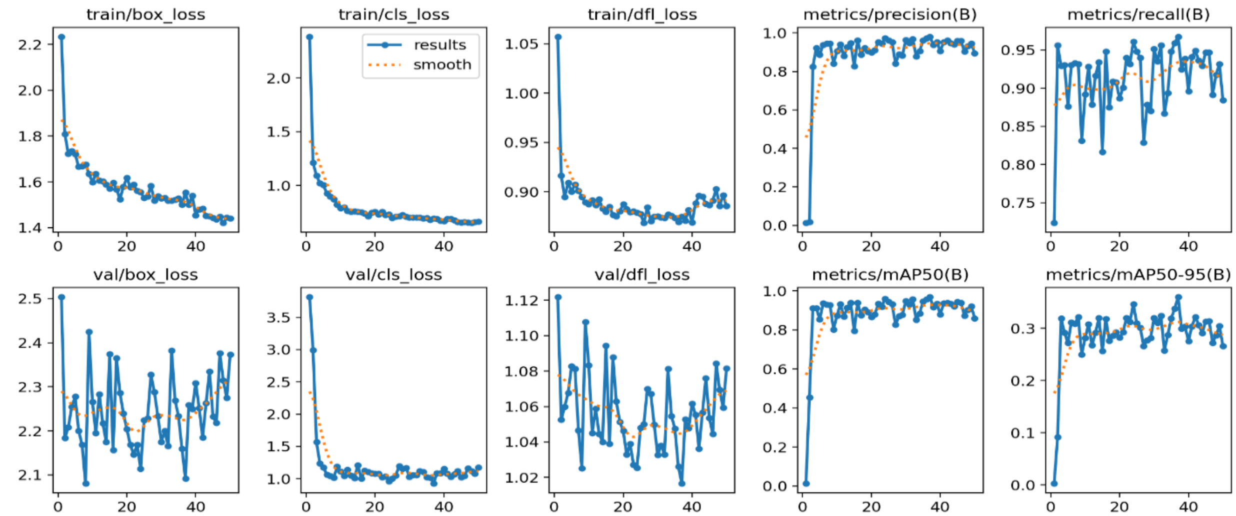

Figure 7. Training results of the YOLO11n model

As shown in Figure 8, the YOLO11n model achieved an mAP@50 value of **0.969**, indicating excellent object detection performance. The PR curve remained close to the upper-right corner of the graph, confirming that the model maintained both high precision and high recall during seed detection.

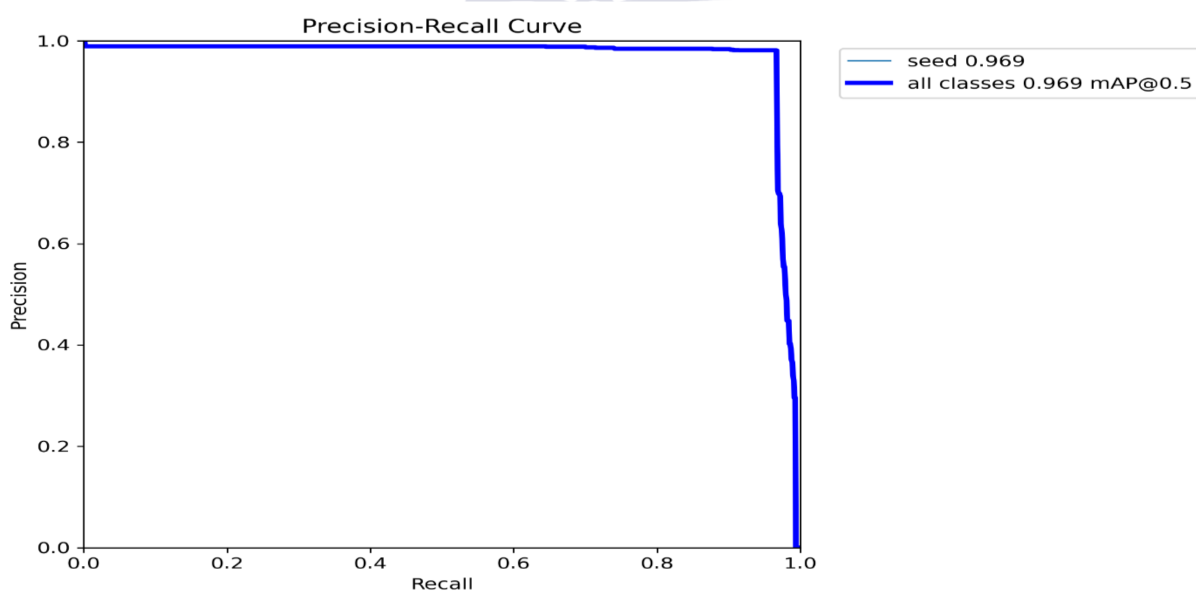

Figure 8. YOLO11n Precision Recall Curve

As illustrated in Figure 9, the YOLO11n model correctly detected 848 canola seed instances while generating only 16 false positives and 16 false negatives. Compared with YOLOv8n, the model produced fewer detection errors and demonstrated better classification consistency. These findings confirm that YOLO11n provides more reliable performance for image-based canola seed detection and counting.

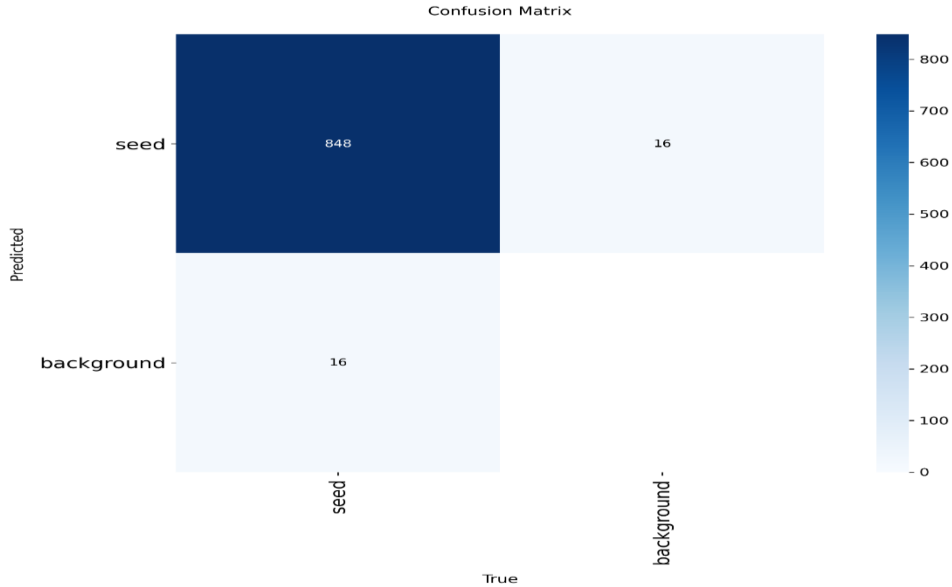

Figure 9. Confusion matrix of YOLO11n on the canola seed validation dataset

The reduction in false positive and false negative detections shows that YOLO11n is more reliable for canola seed counting applications. The improved performance can be attributed to the improved feature extraction and object representation capabilities of the YOLO11 architecture.

4.3 Comparative Analysis

A comparative analysis was conducted to evaluate the relative performance of YOLOv8n and YOLO11n on the canola seed dataset. Both models achieved high detection performance and successfully identified the majority of seeds. However, YOLO11n consistently outperformed YOLOv8n in terms of detection stability and error reduction.

The mAP@50 value increased from 0.965 in YOLOv8n to 0.969 in YOLO11n. Similarly, the best F1 score improved from 0.95 to 0.97. More importantly, YOLO11n significantly reduced false positives from 39 to 16 and false negatives from 20 to 16 (Table 5).

This improvement suggests that YOLO11n provides more accurate localization and classification of canola seeds. Since counting accuracy directly depends on detection performance, the lower number of detection errors makes YOLO11n more suitable for automated seed counting applications.

Table 5. Comparison of YOLOv8n and YOLO11n

Metric	YOLOv8n	YOLO11n
Best F1-Score	0.95	0.97
mAP@50	0.965	0.969
mAP@50-95	0.270	0.266
True Positives	844	848
False Positives	39	16
False Negatives	20	16

YOLO11n outperformed YOLOv8n in most evaluation metrics, including F1-score, mAP@50, false positives, and false negatives. However, YOLOv8n achieved a slightly higher mAP@50-95 value.
The comparison results clearly show the advantage of YOLO11n over YOLOv8n for image-based canola seed detection and counting.
Table 6 presents the percentage improvement achieved by YOLO11n compared with YOLOv8n. The results show that YOLO11n improved the best F1-score by 2.1% and increased mAP@50 by 0.4%, indicating slightly better overall detection performance. More importantly, YOLO11n significantly reduced false positive detections by 58.9% and false negative detections by 20.0%. These improvements demonstrate that YOLO11n provides more stable and reliable seed detection and counting performance. The substantial reduction in detection errors suggests that YOLO11n is better suited for automated canola seed counting applications where accurate object localization and counting are critical.

Table 6. Improvement Percentage

Metric	YOLOv8n	YOLO11n	Improvement
F1	0.95	0.97	+2.1%
mAP@50	0.965	0.969	+0.4%
FP	39	16	-58.9%
FN	20	16	-20%

4.4 Discussion

The results of this experiment confirm the high efficiency of object detection based on deep learning algorithms for automatic canola seed counting. As a result, both versions of YOLO could learn canola seed features from the custom dataset consisting of 833 pictures. These results coincide with findings obtained during previous agricultural object detection experiments involving YOLO architectures. Those works included various object-counting tasks like seeds, wheat ears, soybean pods, and phenotyping crops. According to those experiments, modern versions of YOLO architectures can produce excellent results for small object detection tasks because of efficient feature extraction and multi-scale processing.
As opposed to previous experiments that involved seed counting, the current one has a more practical application and is much less expensive. To detect canola seeds, the proposed framework did not require any special equipment, UAVs, or sensors. All experiments were conducted using a regular smartphone camera under natural lighting conditions.
Despite similar performance, the most robust version of YOLO turned out to be YOLO11n since its error rate was the lowest. As a result, YOLO11n can be considered the most optimal model for canola seed detection and counting tasks.
There are several areas where the framework can be applied, which include seed quality estimation, agriculture phenotyping, crop breeding, automation, and smart farming. Future research can focus on making the algorithm computationally efficient by increasing the size of the dataset and testing it using larger YOLO models or transformers for object detection tasks.
In contrast to YOLOv8n, YOLO11n had a slight decrease in terms of mAP@50-95 but had fewer false positives and false negatives and a better F1-score.
Despite high accuracy obtained from the framework, the data were collected in an environment that provided good lighting and used only one kind of object on a white background. In addition, there was no overlapping seed in the test set. Thus, the framework may perform differently when dealing with overlapping seeds, complex backgrounds, and poor lighting. Future work should be done by testing the model with more diversified data. The dataset included images from one phone and on a white background only.

4. Conclusion and Future Work

The current study proposed an imaging-based deep learning framework towards automated seed detection and counting by employing YOLOv8n and YOLO11n object detection models. An 833-image database was built using images of canola seeds exposed to natural sunlight. Manual annotation was performed for all the seeds using the CVAT tool. There were different seed arrangements within the database, with images containing between one and ten seeds, and a partitioning of the dataset into training and validation sets was performed.

Experimental findings indicate that both the YOLOv8n and YOLO11n models delivered impressive performance results on the created customized dataset for canola seed recognition. In particular, the mAP@50 result for YOLOv8n was 0.965, with the optimal F1 score being 0.95, whereas YOLO11n had a mAP@50 of 0.969 and an optimal F1 score of 0.97. Moreover, YOLO11n made fewer mistakes than YOLOv8n in terms of false positive and false negative detection, which suggests its improved accuracy. Comparison demonstrates that YOLO11n performs better than YOLOv8n.

This approach presents an effective, economical, and efficient way of conducting automatic seed counting from RGB images captured by a smartphone's camera. Contrary to most of the previous works that required the use of UAVs, hyperspectral cameras, or other specific imaging systems, the suggested methodology can be efficiently adopted in laboratories, seed testing centers, and research stations in agriculture. There exist numerous possibilities for the application of the suggested system in assessing seed quality, crop breeding projects, agricultural phenotyping, seed germination, and other aspects of smart agriculture.

Despite presenting a remarkable success, there is much more room for improvement in terms of implementing the proposed approach. One of the directions for future work might include building a larger database based on collecting images from different conditions and lighting scenarios. Also, one could explore the possibility of using more sophisticated YOLO networks, Transformer detectors, and attentional mechanisms for better detection of seeds. Another possibility for improving the detection process is implementing the detection framework in mobile or web applications.

5. Data and Code Availability

The dataset and source code used in this study are not publicly available at the time of publication. However, they may be made available by the corresponding author upon reasonable request for research and academic purposes.

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