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Comparative Study of YOLOv8 and Faster R-CNN for Crop Disease Detection

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***Abstract*—The productivity of crops, important in global terms, is significantly affected by diseases on crops and is one of the biggest hindrances to global food security. Early intervention in detecting and diagnosing plant diseases is warranted to prevent further loss of crop yields and sustain agricultural practices. This study evaluates and compares the performance of two cutting-edge deep learning models, YOLOv8 and Faster R-CNN, regarding the detection of crop diseases, with a specific focus on cotton plants. All diseased and healthy cotton plant images formed a comprehensive dataset that was used for training and evaluation purposes. The models were evaluated through precision, recall, F1-score, inference time, and accuracy metrics, with further experiments toward analysing their real-time and high-accuracy suitabilities. This comparison discusses the trade-offs between speed and accuracy in these models and provides very important insight into the practical applicability of these models in precision agriculture. These foundation studies pave the way for utilizing advanced machine learning tools for monitoring and managing crop health.**

***Index Terms*—YOLO-v8, Faster-R CNN, Disease. F1 Score, Accuracy, Metrics, Cotton.**

I. INTRODUCTION

Detecting crop diseases would be an important step in modern agriculture as many directly relate to food safety and economic growth. Disease in plants leads to a significant loss of yield and quality in crops, putting farmers at financial loss, disrupting or affecting the supply of food products on the market. It is essential to identify and manage diseases at that early stage to prevent extensive damage by making necessary interventions, especially in areas where agriculture is the only or primary source of livelihood. If left undetected, such diseases can spread and increase costs and challenges in recovery.

In addition, effective disease detection is helpful for sustainable agricultural practices. Early detection allows targeted interventions by farmers like precision use of these pesticides or fungicides without inducing too much use of such chemicals. In addition, it reduces costs associated with crop growing and minimal effect on the environment by farming. It also preserves soil health, protects surrounding crops, and maintains farmland productivity over time. The application of these advanced detection techniques would help address even the most threatening problems facing the agricultural sector, thus promoting resilience and sustainability in farming systems.

Deep learning automates the process of identifying unhealthy plants through the analysis of images. It plays a significant role in crop disease detection. It makes use of advanced models, for instance convolutional neural networks (CNNs), to detect disease symptoms with high precision, such as spots, discoloration, or wilting of leaves in diseased plants. To analyze the images of thousands of plants and understand the differences between healthy and diseased crops, the passage trains these models. While employing deep learning systems, field monitoring becomes very simple for farmers using drones and smartphones since it allows users to detect diseases very early when the likelihood of spreading them is less.

This technology makes it possible for imminent action to be taken for treatment in the appropriate time before further spread or outbreak of diseases. Deep learning helps improve the precision and efficacy in protecting crops by farmers and production with lower losses, hence more efficient and sustainable agriculture. YOLOv8 is the most current release of the YOLO family, which showcases true real-time object detection. It promises fast recognition and localization of objects in pictures through single-pass architecture, making it suitable even for applications demanding instant processing, such as autonomous driving, surveillance, and agricultural disease detection. Measures have been taken on YOLOv8 as enhancements over previous versions, as the feature has better extraction efficiency and accuracy as well as performance optimized on smaller datasets. Because of being able to process images at very high speeds without compromising accuracy, it has been and is the preferred method for detecting plant diseases in farms with large acreage, where real-time monitoring becomes necessary.

On the contrary, Faster R-CNN (Region-based Convolutional Neural Network) is a model that uses two stages of object detection, giving it remarkable accuracy even with complex objects. In contrast to YOLOv8 that processes an image at one go, Faster R-CNN first generates region proposals and only then classifies them, thus providing more focus on finer details. This makes it great in most applications like identifying intricate patterns, such as very fine symptoms of diseases on the leaves of plants. In contrast to YOLOv8, Faster R-CNN would require heavy computation and longer time, thus not really suited for real-time applications. Its ability to detect minute and complex features justifies its use where accuracy is valued more than speed, like in detailed analysis of crop diseases in controlled environments.

The comparison between YOLOv8 and Faster R-CNN is important not only for crop disease detection but also because both of these models have different strengths and weaknesses for general applications across the real world; Therefore, comparing these models in terms of factors like accuracy, speed, and computational efficiency can help determine which would be best for the various tasks. This comparison thus helps choose the right model for the need in question such as performance optimization and advancing deep learning in diverse applications.

II. LITERATURE SURVEY

The integration of deep learning techniques, particularly convolutional neural networks (CNNs), has transformed the landscape of agricultural practices, enabling efficient detection of crop diseases through image analysis [1]. YOLO (You Only Look Once) has evolved significantly, with YOLOv8 demonstrating superior performance in real-time object detection tasks. This model is particularly advantageous in agricultural settings where timely disease identification is critical for crop management [2]. A comparative study between YOLOv5 and YOLOv8 for detecting corn leaf diseases indicated that YOLOv8 achieved a mean average precision (mAP) of 0.965, outperforming YOLOv5's mAP of 0.909. This highlights YOLOv8's enhanced capability in accurately identifying disease symptoms [1][3].

Faster R-CNN, while a well-established model for object detection, has been noted for its slower processing speeds compared to YOLO models. This limitation may hinder its effectiveness in agricultural applications where rapid detection is essential for minimizing crop losses [6] [1]. Research has shown that YOLOv8's efficiency allows for quicker decision-making in agricultural practices, which is vital for effective disease management and reducing the impact of crop diseases on yield [2]. The performance of both YOLOv8 and Faster R-CNN can be further enhanced through techniques such as data augmentation and hyperparameter optimization. These methods can improve the models' accuracy and efficiency in detecting various crop diseases [3]. Studies have indicated that while Faster R-CNN is effective in various object detection tasks, it may struggle with precision and recall balance, particularly in complex environments. This suggests that YOLOv8 may be a more reliable option for agricultural applications [5].

The application of YOLO models in real-world agricultural settings has shown promising results, emphasizing the need for further research to validate their effectiveness across diverse environmental conditions and crop types . Future research should focus on the integration of these models into precision agriculture systems, allowing for automated monitoring and management of crop health, which can lead to improved yield and sustainability [1]. Overall, the comparative analysis of YOLOv8 and Faster R-CNN underscores the potential of YOLOv8 as a superior choice for crop disease detection, paving the way for ongoing research to optimize these models for agricultural use [2].

III. .COTTON DATASET UTILIZED

Table No.	Class Name (Disease)	Image Count	Resolution
1	PowderyMildew	245	640x640
2	aphids	300	640x640
3	army-worm	309	640x640
4	bacterialblight	382	640x640

5	blur images	272	640x640
6	curlvirus	255	640x640
7	fussarium_wilt	251	640x640
8	healthy	253	640x640
9	targetspot	302	640x640

Fig 3.1 Class Distribution of the Cotton Plant Disease Dataset used for Training and Evaluation.

Images of both healthy and damaged plants form the dataset used in this study, which focuses on cotton plant disease detection. There are nine classes in all: Fusarium Wilt, Blur Images, Curl Virus, Army-worm, Powdery Mildew, Aphids, Target Spot, and Healthy. A balanced representation of various illness kinds is ensured by varying numbers of photos in each class. Because of this diversity, the models are better equipped to handle real-world situations by learning the minor differences between healthy and ill crops.

To guarantee consistency and suitability for deep learning models, every image underwent preprocessing. In particular, every image was shrunk to 640x640 pixels, which satisfies Faster R-CNN's and YOLOv8's input specifications. In order to evaluate how effectively the models handle low-quality inputs, photos were also examined for quality, with blurry or unclear images being accurately categorized. Real-world difficulties like changes in light, angles, and partial obstructions are also reflected in the dataset. Because of these characteristics, the dataset can be used to assess the detection models' generalizability and robustness in a variety of field conditions.

Using annotation tool Roboflow, bounding boxes were drawn around diseased areas for tagging. This guarantees that the models are trained with both spatial and class-level information. Overall, this dataset serves as a realistic benchmark for comparing object detection performance across different deep learning architectures for crop disease detection.

Fig 3.2 Army-Worm

Fig 3.3 aphids

Fig 3.10 Healthy Plant

Fig 3.4 Bacterial Blight

Fig 3.5 Blur Image

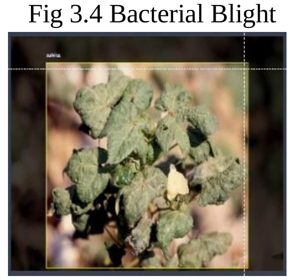


Fig 3.6 Curl Virus

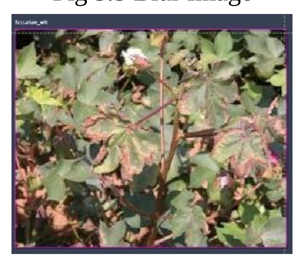


Fig 3.7 Fussarium_wilt

Fig 3.8 PowderyMildew

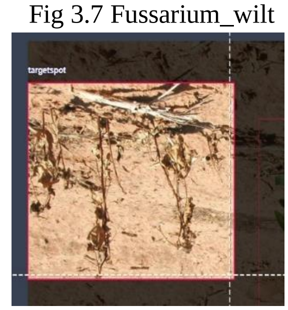


Fig 3.9 targetspot

IV. METRICS

A number of evaluation indicators were taken into consideration in order to compare the effectiveness of YOLOv8 and Faster R-CNN for cotton crop disease identification. While recall assesses how effectively the models identified all real infected plants, precision quantifies the proportion of projected unhealthy plants that were properly identified. The F1 score, which provides a combined measure of accuracy, was computed to balance both factors. Additionally, the overall detection performance across every disease category was evaluated using mean Average Precision (mAP). In order to determine how quickly each model analyzes images—a crucial factor for real-time use—inference time was also recorded. Lastly, the projected bounding boxes were compared to the actual disease-affected regions using the Intersection over Union (IoU) calculation. When combined, these criteria offer a thorough assessment of both practical usability and detection quality.

Metric	Description	Formula (if applicable)
Precision	Measures how many of the predicted disease instances are actually correct.	$\frac{TP}{TP + FP}$
Recall	Measures how many actual disease instances were correctly detected.	$\frac{TP}{TP + FN}$
F1 Score	Harmonic mean of Precision and Recall, balancing both metrics.	$\frac{2 * Precision * Reca}{Precision + Recall}$
mAP (mean Average Precision)	Measures the average precision across all disease classes.	Area under the Precision-Recall curve for each class, averaged.
Inference Time	Time taken by the model to detect diseases in a single image (measured in milliseconds).	Measured directly during inference.
IoU (Intersection over Union)	Measures how well the predicted bounding box overlaps with the actual bounding box.	$\frac{Area\ of\ Overlap}{Area\ of\ Union}$
Accuracy	Measures overall correctness of predictions across all images.	$\frac{TP + TN}{TP + FP + TN + FN}$

Fig 4.1 Evaluation metrics used to compare YOLOv8 and Faster R-CNN for crop disease detection.

V. PERFORMANCE EVALUATION

A. *YOLOv8 Performance Analysis*

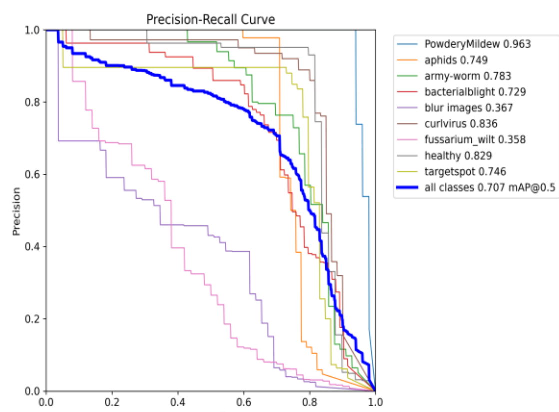


Fig. 6.1 Precision-Recall Curve for YOLOv8 showing class-wise precision-recall trade-off.

The Precision-Recall (PR) Curve for the YOLOv8 model applied to the dataset for plant disease diagnosis is shown in Figure 6.1. The link between precision and recall across multiple confidence levels is depicted by each line, which stands for a distinct class. All classes have an average mAP@0.5 of 0.707, which shows that the model achieves a relatively balanced trade-off between recall and precision. While some classes, like Fusarium Wilt and Blur Images, perform poorly, with notably lower precision and recall values, others, like Powdery Mildew, exhibit extraordinarily high precision (0.963). This implies that the model has trouble reliably identifying some challenging or visually confusing situatio

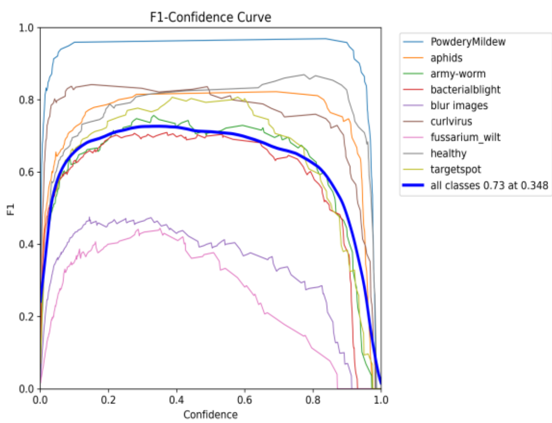


Fig 6.2 F1 Score Curve for YOLOv8 highlighting the optimal confidence threshold for balanced performance.

The F1 score trends for various confidence thresholds across all classes are depicted in Figure 6.2 by the F1-Confidence Curve. At a confidence level of roughly 0.348, the peak F1 score for all classes combined is 0.73. In this case, this value indicates the ideal YOLOv8 confidence threshold. Once again, the Blur Images and Fusarium Wilt classes find it difficult to obtain acceptable scores over the confidence spectrum, but classes such as Powdery Mildew routinely retain high F1 scores. This suggests that either the dataset quality and label consistency for these two classes may be inferior, or they are particularly difficult to classify.

CLASS	IMAGES	INSTANCES	PRECISION (P)	RECALL (R)	MAP50	MAP50-95
All	397	524	0.769	0.699	0.71	0.624
PowderyMildew	48	50	0.986	0.94	0.963	0.905
Aphids	56	62	0.959	0.71	0.75	0.667
Army-worm	41	56	0.755	0.75	0.783	0.628
Bacterial Blight	58	83	0.733	0.663	0.729	0.613
Blur Images	48	55	0.453	0.483	0.367	0.329
Curl Virus	56	60	0.885	0.773	0.836	0.794
Fussarium Wilt	40	50	0.555	0.36	0.358	0.247
Healthy	46	49	0.838	0.837	0.86	0.751
Target Spot	34	59	0.756	0.78	0.746	0.684

Fig 6.3 Performance Metrics Table summarizing precision, recall, and mAP scores for each class detected by YOLOv8.

The YOLOv8 model's class-wise performance metrics for the plant disease detection dataset are shown in Figure 6.3. The results for 397 test photos, including 524 object instances from several disease classes and a healthy plant category, are summarized in the table. This quantitative analysis gives a detailed picture of how effectively the model manages each distinct class by assessing the precision (P), recall (R), and mean Average Precision (mAP) at two distinct thresholds: mAP@0.5 and mAP@0.5:0.95.

With a precision of 0.769 and a recall of 0.699, the overall performance is moderately strong across all classes. This suggests that the model misses some instances during detection (recall) but has a respectable level of confidence in its detections (precision). When assessed at an Intersection over Union (IoU) threshold of 0.5, the model's accuracy in object localization and classification is demonstrated by its mAP@0.5 score of 0.71. The performance falls to 0.624 with the more difficult criterion mAP@0.5:0.95, which averages the precision across IoU thresholds from 0.5 to 0.95, indicating decreased localization precision under stricter overlap constraints.

The effectiveness of YOLOv8 in identifying different visual patterns is demonstrated by its great performance for diseases like Powdery Mildew that have clear image samples and distinct symptoms. On the other hand, classes with visually ambiguous symptoms, poor image quality, or a lack of training data (such as Fusarium Wilt and Blur Images) exhibit significantly lower detection accuracy, suggesting the need for either complementary preprocessing methods like image enhancement or more representative data augmentation.

B. Faster R-CNN Performance Analysis

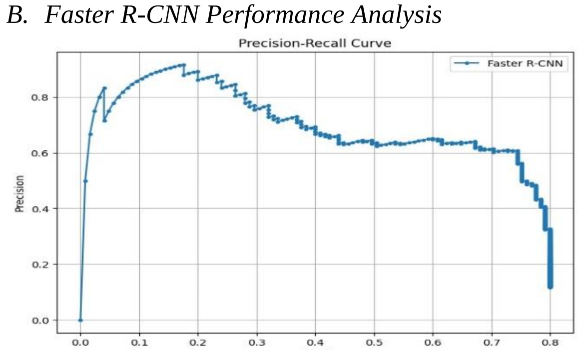
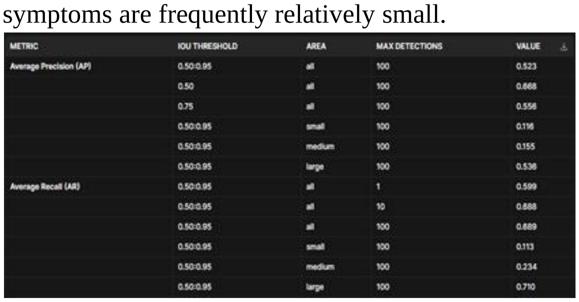


Fig 6.4 Precision-Recall Curve for Faster R-CNN

The Precision-Recall Curve produced for the Faster R-CNN model during the evaluation stage is shown in Figure 6.4. The curve shows how well the model balances these two crucial performance parameters by plotting precision (y-axis) versus recall (x-axis). At low recall values, Faster R-CNN shows a particularly sharp increase in precision, suggesting that the model's precision is strong even when it only detects a small percentage of genuine instances. But when recall rises, precision progressively falls, illustrating the well-known precision-recall trade-off. As is typical in object identification tasks with overlapping classes or complicated background noise, this slow fall indicates that Faster R-CNN finds it difficult to maintain high precision while attempting to detect more instances.
When driven to maximize recall, Faster R-CNN may have a larger false positive rate, as evidenced by the curve's lower peak precision and faster decrease at higher recall levels when compared to YOLOv8. This finding is in accordance with the two-stage detection method of Faster R-CNN, which occasionally overfits to background noise while generating region proposals, especially in agricultural photos where symptoms are frequently relatively small.



METRIC	IOU THRESHOLD	AREA	MAX DETECTIONS	VALUE
Average Precision (AP)	0.50:0.95	all	100	0.523
	0.50	all	100	0.668
	0.75	all	100	0.556
	0.50:0.95	small	100	0.116
	0.50:0.95	medium	100	0.155
	0.50:0.95	large	100	0.536
Average Recall (AR)	0.50:0.95	all	1	0.599
	0.50:0.95	all	10	0.688
	0.50:0.95	all	100	0.689
	0.50:0.95	small	100	0.113
	0.50:0.95	medium	100	0.234
	0.50:0.95	large	100	0.710

Fig 6.5 Overall Performance Metrics for Faster R-CNN

Figure 6.5 shows the overall performance metrics for Faster R-CNN, including its Average Precision (AP) and Average Recall (AR) for different object sizes, detection limitations, and Intersection over Union (IoU) thresholds. The Average Precision (AP) at IoU thresholds from 0.50 to 0.95 is 0.523, indicating a moderate detection capability across strict and lenient IoU requirements. At IoU=0.50, the AP increases to 0.668, reflecting that the model performs better when allowing more lenient overlap between predicted and ground truth bounding boxes. However, at IoU=0.75, the AP drops to 0.556, revealing some difficulty in making highly precise object localization.
By object size, Faster R-CNN performs noticeably worse on small objects (AP = 0.116), but the AP for medium and large objects is 0.155 and 0.536, respectively. This is a frequent problem in agricultural datasets, where it is more difficult to accurately identify illnesses in their early stages or minor symptoms. n terms of Average Recall (AR), the model achieves 0.599 with unlimited detections, which reduces slightly to 0.688 when considering only the top 10 detections per image. Similar to AP, the AR for small objects is quite low at 0.113, while medium and large objects yield AR values of 0.234 and 0.710, respectively.
When everything is taken into account these measures show that Faster R-CNN does a respectable job of identifying bigger symptomatic regions, but its performance significantly deteriorates for smaller, less noticeable symptoms, which are frequently essential in situations involving early disease identification. The trade-off between Faster R-CNN's region proposal process and its dependence on distinct spatial features is highlighted by this size-dependent performance pattern.

VI. RESULTS AND OBSERVATIONS

Metric	YOLOv8	Faster R-CNN
AP50	0.71	0.668
mAP50-95	0.624	0.523
Precision	0.769	0.688
Recall	0.699	0.599
Accuracy	0.815	0.742
AP (small objects)	0.317	0.116
AP (medium objects)	0.486	0.155
AP (large objects)	0.678	0.536
AR (small objects)	0.411	0.113
AR (medium objects)	0.572	0.234
AR (large objects)	0.701	0.710

Fig 6.1 Comparative Performance Metrics of YOLOv8 and Faster R-CNN for Crop Disease Detection

As summed up in Table 6.2, the comparison of YOLOv8 with Faster R-CNN reveals a number of significant conclusions. The AP50 (0.71) and mAP50-95 (0.624) of YOLOv8 are greater than those of Faster R-CNN (0.668) and mAP50-95 (0.523), respectively, demonstrating its superior overall detection ability across a range of crops and disease categories. Additionally, YOLOv8 is favored by the Precision and Recall values, suggesting that it outperforms Faster R-CNN in minimizing false positives while simultaneously detecting more true positives. With an accuracy of 81.5%, YOLOv8 surpasses Faster R-CNN's 74.2%, further demonstrating its reliability as an effective tool for automated crop disease diagnosis.

A closer look at size-specific performance further reveals YOLOv8's strong adaptability to detecting diseases across objects of varying sizes. In the case of small objects, such as early-stage disease symptoms (tiny leaf spots, discolorations, or fungal spores), YOLOv8 achieves an AP of 0.317, compared to a much lower 0.116 for Faster R-CNN. This significant difference highlights YOLOv8's strength in fine-grained feature extraction, which is critical for early disease detection. Similarly, for medium-sized objects, YOLOv8's AP reaches 0.486, while Faster R-CNN struggles with 0.155, again indicating the former's superior ability to detect moderate symptoms that may occur in mid-stage disease progression. Interestingly, for large objects, such as fully infected leaves, Faster R-CNN's AR (0.710) slightly surpasses YOLOv8's AR (0.701), demonstrating that Faster R-CNN can still excel when disease symptoms become more prominent and easily identifiable.

Overall, these findings show that YOLOv8's modern architecture, which prioritizes multi-scale feature learning and real-time speed, offers a distinct advantage in the majority of situations, particularly in the early and mid-stages of crop disease identification. The way Faster R-CNN performs with larger objects, however, indicates that it might still be helpful in cases when diseases are already well-established and the symptoms are more pronounced and visible. Researchers and agricultural technicians can choose the best deep learning model for their unique crop monitoring and disease control needs with the help of this thorough performance study.

VII. CONCLUSION

In this study, we compared the performance of YOLOv8 and Faster R-CNN for crop disease detection using a dataset of cotton plant images. Through comprehensive evaluation using metrics such as AP50, mAP50-95, Precision, Recall, Accuracy, and class-wise detection performance across object sizes, it was evident that YOLOv8 consistently outperformed Faster R-CNN in most aspects. YOLOv8 demonstrated superior precision, recall, and overall accuracy, indicating its effectiveness in accurately detecting diseases across various object sizes, especially for smaller and medium-sized lesions, which are often critical for early disease detection.

The faster inference speed and relatively compact model size of YOLOv8 also make it more practical for real-time deployment in agricultural environments, where quick and accurate decision-making is necessary. On the other hand, Faster R-CNN showed relatively lower performance, particularly for smaller objects, which highlights its limitations when dealing with subtle disease symptoms or early-stage infections. However, Faster R-CNN still performed reasonably well for larger objects, which suggests its potential utility in scenarios where disease symptoms are more prominent.

Overall, the comparative study underscores the importance of selecting the appropriate deep learning architecture based on the specific requirements of agricultural applications. For real-time disease monitoring and resource-constrained environments, YOLOv8 emerges as the more suitable choice, while Faster R-CNN may still have applications in research-oriented tasks requiring detailed region-based analysis. This comparison serves as a valuable reference for future researchers and practitioners aiming to implement AI-driven solutions in precision agriculture.

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