

# AI-Based Weed Detection Algorithm using YOLOv8

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## Abstract

The development of a country relies heavily on agricultural produce and its related sectors. However, farmers face significant challenges due to the uncontrolled growth of weeds, which reduces their yield. Weed detection is a key step in the removal process, and advances in technology, such as the YOLOv8 model, have simplified this task. YOLOv8 offers improved weed and crop detection, with enhancements of 1.3% and 1.17% in mAP50 and mAP50-95, respectively, over the previous YOLOv5 model. This allows farmers to efficiently identify and eliminate weeds, leading to higher productivity and better crop yields, ultimately supporting the agricultural growth of the country.

*Keywords:* Agriculture, Artificial Intelligence, Weed Detection, YOLOv8

## 1. Introduction

Weeds are the primary reason for the reduced production of agricultural produce on farms. It is estimated that over 43% of crop losses in farms are caused by weeds which is a huge amount of loss. It is therefore imperative to get rid of the weeds in an agricultural farm. The most significant and basic step in this process of weed elimination from an agricultural farm involves the process of weed detection. The classical and traditional process of weed removal is cumbersome and can sometimes result in the elimination of useful crops. Hence it is very crucial to ensure a reliable and efficient method to detect and eliminate these crops. The traditional image processing techniques involve the analysis of the morphological features of the weed to ensure the detection of the weeds [1]. This process involves a large amount of time. It can be forced to undergo bias which makes it ineffective to implement thereby creating a need to search for a more efficient method to ensure a sustainable process for weed detection. A combination of deep learning algorithms have been used by authors of [2] have utilized the ResNeXt feature extraction along with a Faster R-CNN model to ensure efficient weed detection. The introduction of YOLOv8 by Ultralytics offers greater performance than its predecessors like YOLOv5 and its associated models [3].

## 2. Literature Review

Faisal Ahmed et al. studied the separation of weeds from crops in digital photos with the help of support vector machines (SVM) and Bayesian classifiers. It was

observed that the SVM classifier performs better than the Bayesian classifier. A weed-detecting device powered by solar panels was utilized. The machine consisted of a camera installed at the base for continuous image capture, and it was mobile to help in the movement between crop rows [4]. The paper [5] by Liu et al. (2021) displays a deep learning-based system for weed detection in crops based on Unmanned Aerial Vehicle imagery. The authors employed a modified version of the Faster R-CNN model to detect and classify weeds in the images. The system had successfully achieved high accuracy in weed detection. The authors of the paper [6] employed techniques of CNN and Res-Net 50 algorithms on a dataset to efficiently classify weeds and crops. The results show that the Res-Net 50 algorithm outperforms the CNN model with an output of 84.6% and 90% accuracy on two different datasets of cucumber and onion respectively. The U-Net-MobileNetV2 architecture is utilized in [7] to achieve accurate and efficient detection of weeds while reducing computational costs. The methodology proposed in this study has illustrated a 96% accuracy. The experiment conducted in paper [8] uses the ADAM optimizer on a four-class weed dataset showing a 96.58% accuracy in classifying and categorizing weeds in a field. In the paper [9] the authors have employed the technique of using CNN which will thereby help to demonstrate the effectiveness of deep learning models to help in efficient weed detection and classification. This research in [10] represents an integrated method for transforming farming by combining robots, the Internet of Things (IoT), and environmental protection. The Machine learning

Convolutional Neural Networks (CNNs) algorithm has been combined for focused and efficient treatment.

### 3. Methodology

The process of employing the YOLOv8 model to efficiently classify weeds and crops includes various steps. The primary step involves isolating and collecting a dataset that can be suitably engineered to help in the ease of training. The dataset was received from an open-source tool online [11]. The dataset was further annotated to help in the efficient classification of the weed and crop to improve the training metrics while employing the YOLOv8 model. Before training the model, certain elementary steps were involved which included importing the Ultralytics and YOLO libraries. The training included using the ADAM optimizer and training it for an epoch size of 100 with a worker size of 4 and a comprehensive batch size of 16 and included a freezing time of 10 ms to ensure an efficient training of the dataset under the YOLOv8 model. The trained model was allowed to be evaluated by passing it under a validation and testing dataset to verify and isolate the results produced by the model. The evaluation metrics of Precision, Recall, and IoU have been generated to produce an analysis of the model which has been trained on the given weed dataset as shown in Eq. [1], [2] and [3], respectively.

$$Precision = TP / (TP + FP) \tag{1}$$

$$Recall = TP / (TP + FN) \tag{2}$$

$$IoU = (\text{Area of Intersection}) / (\text{Area of Union}) \tag{3}$$

After training and testing this model suitable validation and testing dataset the results and the findings were reported to justify the utility of this model to ensure a clear classification of weed and crop dataset. Fig. 1 shows the training of the model under YOLOv8 for 100 epochs while Fig. 2 shows the visual representation of the entire run history of the training model.

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
1/100	1.26	3.044	3.644	3.346	46	640: 100%
144/144	[00:25:00:00, 5.40bit/s]					
Class Images Instances Box(P R mAP50 mAP50-95):						
100% [7/7 [00:02:00:00, 2.52it/s]						
all 220 378 0.521 0.0811 0.0112 0.00335						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
2/100	1.126	2.491	3.336	2.762	38	640: 100%
144/144	[00:23:00:00, 6.22it/s]					
Class Images Instances Box(P R mAP50 mAP50-95):						
100% [7/7 [00:01:00:00, 3.82it/s]						
all 220 378 0.0384 0.196 0.0163 0.0048						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
3/100	1.116	2.364	3.194	2.609	44	640: 100%
144/144	[00:23:00:00, 6.18it/s]					
Class Images Instances Box(P R mAP50 mAP50-95):						
100% [7/7 [00:01:00:00, 4.93it/s]						
all 220 378 0.587 0.138 0.0629 0.021						
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
4/100	1.116	2.273	3.115	2.496	35	640: 100%
144/144	[00:23:00:00, 6.18it/s]					

Fig. 1. Training of the model under YOLOv8 for 100 epochs

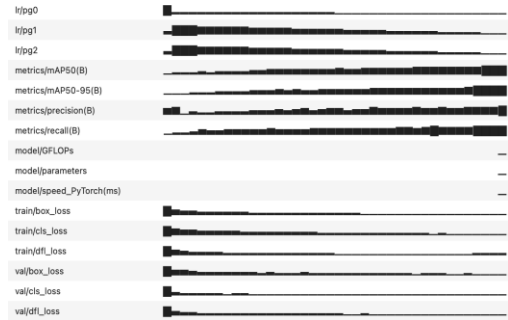


Fig. 2. Visual representation of the entire run history of the training model

The flowchart in Fig. 3 gives a lucid description of the processes involved in the training and running of this model to efficiently classify the weeds and crops in the given dataset.

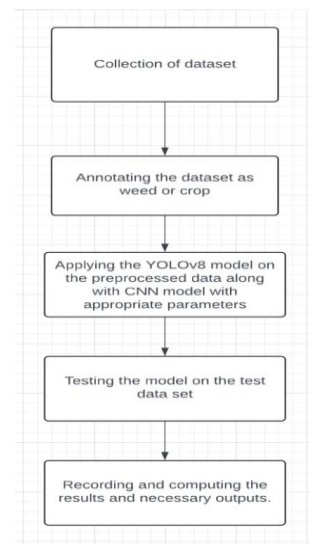


Fig. 3. Flow of processes of the training and testing of the YOLOv8 model.

### 4. Results

After employing the YOLOv8 model on the given dataset. The classification has occurred successfully indicating a successful construction and testing of the model. Fig. 4 shows a clear and distinct classification between weeds and crops where 0- crops and 1- indicates the crops. The image in Fig. 5 signifies the precision-confidence curve at different thresholds. Fig. 6 establishes the graphical representation of the recall-confidence curve. The table shown in Fig. 7 establishes the cumulative values of all the metrics taken for this classification.

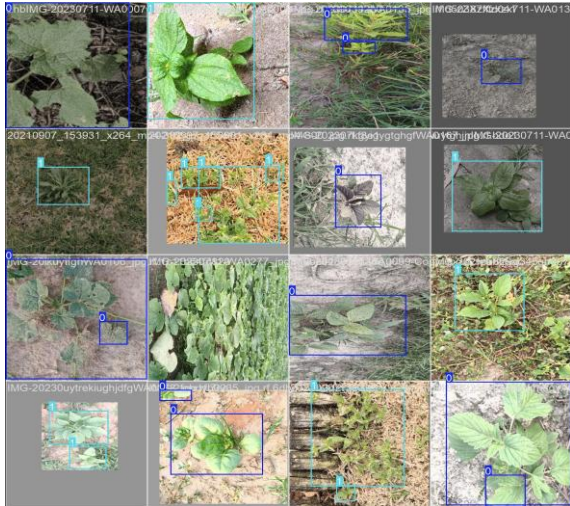


Fig. 4. Classification between weeds and crops where 0- crops and 1- indicates the crops.

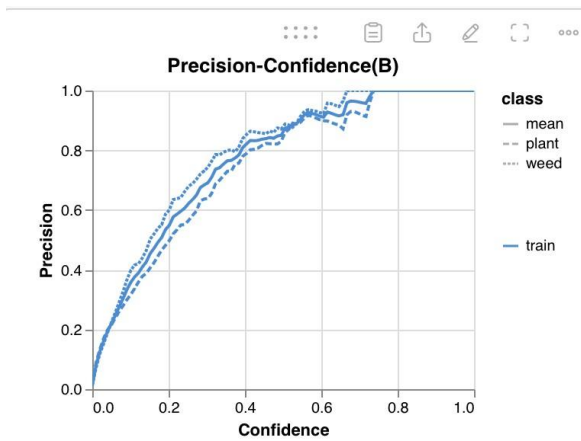


Fig. 5. Precision-confidence curve at different thresholds.

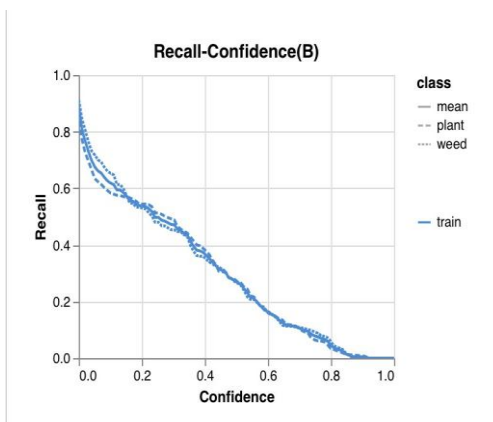


Fig. 6. Recall-confidence curve.

S.no	Metric	Value
1	Precision	0.9895
2	F1-score	0.9483
3	mAP-50	0.9564

Fig. 7. Cumulative values of all the metrics taken for this classification.

### 5. Conclusion:

The objective of conducting this experiment using the YOLOv8 on the given weed dataset was to ensure an efficient and computationally less intensive method to classify and precise classification rate of 0.9895 which indicates a highly accurate and successful classification. The graphical representation of precision and confidence indicates that precision values almost attain a near-perfect maximum while plotting the confidence at different thresholds which shows a significant growth at every threshold. Therefore, we can conclude that the above-mentioned YOLOv8 model is a very clear and imperative model for classifying weeds and crops thereby acting as a suitable means to help in the primary step of weed classification and detection.


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