Research Article

Implementation of Automated Weed Detection using Computer Vision Techniques

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ABSTRACT

Agriculture is one of the most ancient and most important professions forming the base of any society. The development of any country depends on the agricultural produce and its related areas to ensure greater growth in the country. One of the major problems affecting the agricultural produce of farmers worldwide is the unrestricted growth of weeds in the farm and agricultural areas which results in reduced produce for the farmers. One of the most elementary steps in the process of weed removal involves the detection of weeds in a field filled with agricultural produce. This process has been made easy by implementing the YOLOv8 process, which has produced great results ensuring easy detection of weeds and crops, making it easier and efficient for the farmers to increase and enhance their produce. YOLOv8 offers improved weed and crop detection with a precise classification rate of 0.9895 which indicates a highly accurate and successful classification. 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. This model can ensure easier, more efficient, and enhanced detection to improve the process of identifying the weeds and thereby eliminating them.

1. Introduction

Automated weed detection has become essential in precision agriculture, aiming to improve crop yields, minimize herbicide use, and support sustainable farming practices. Traditional weed removal processes tend to eliminate useful crops along with weeds, which makes these traditional methods unreliable. Therefore, it is dire to have a reliable technique to detect and remove crops that inhibit the growth of useful plants. Also, in traditional approaches to weed detection using image processing, the analysis involves the morphometric features of the weed with focus on its shapes [1]. The integration of computer vision techniques with machine learning and deep learning algorithms has significantly revolutionized weed detection systems, making them more efficient and effective than ever before. A combination of deep learning algorithms has been used by authors of [2] have utilized the ResNeXt feature extraction along with a Faster R-CNN model to ensure efficient weed detection. Ultralytics introduction of YOLOv8 brought improvements over previous versions such as YOLOv5 and associated models, further increasing overall performance [3].

2. Literature Review

Automated weed identification through computer vision methods has become a key focus in precision agriculture, tackling the difficulties of manual weed control. The application of machine learning and deep learning techniques has greatly improved the precision and effectiveness of weed detection, leading to decreased labor expenses and lower herbicide consumption. Established methods like BRISK and SIFT have been employed for extracting features, with research showing their success in distinguishing between weeds in crops such as ginger and sugarcane [4]. Faisal Ahmed et al. explored the identification of weeds and crops in digital imagery using machine learning techniques, specifically Support Vector Machines (SVM) and Bayesian classifiers. Their findings revealed that the SVM model delivered superior classification accuracy compared to the Bayesian approach. To facilitate automated detection, they employed a solar-

powered mobile unit fitted with a base-mounted camera, enabling continuous image capture as it navigated through crop rows [5]. Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Transformer-based models, have gained prominence in recent years due to their ability to handle complex image data. Studies have demonstrated that CNN-based models achieve high accuracy in weed detection, especially when trained on large and diverse datasets [6]. CNNs and Transformer-based models have shown superior performance in weed classification tasks, particularly in soybean crops [6]. However, this work does not focus on identifying multiple weeds in one image. The paper [7] by Liu et al. (2021) proposed a deep learning framework for weed recognition using aerial imagery obtained from drones. Their system, built on an enhanced Faster R-CNN model, demonstrated high precision in detecting and categorizing weeds in agricultural fields. Another study adopted both Convolutional Neural Networks (CNN) and ResNet-50 to classify crops and weeds. Their results highlighted ResNet-50's superior performance, achieving classification accuracies of 84.6% for cucumber fields and 90% for onion fields [8]. In a separate study, the integration of U-Net with MobileNetV2 offered a resource-efficient solution for weed detection, yielding 96% accuracy while optimizing computational resources [9]. Another experiment utilized the ADAM optimizer on a four-class weed dataset, achieving a classification accuracy of 96.58% [10]. Furthermore, research employing CNNs further confirmed the potential of deep learning for effective weed identification and classification [11]. Another study showcased a comprehensive agricultural automation system combining CNNs, robotics, the Internet of Things (IoT), and environmental monitoring technologies to improve targeted weed control and sustainable farming [12][13].

3. Methodology

To achieve accurate crop and weed classification using the YOLOv8 architecture, a systematic approach is essential. Initially, a curated and simplified dataset was sourced from an open-access platform [14] to streamline the training process. This dataset was then refined to improve its suitability for YOLOv8-based classification tasks. Prior to model training, necessary libraries such as Ultralytics and YOLO were installed to configure the training environment.

For optimal training performance, the ADAM optimiser was selected, with hyperparameters set as follows: 100 training epochs, 4 worker threads, a batch size of 16, and a 10-millisecond freeze interval. These settings enabled efficient processing of the dataset. Upon completing training, the model's robustness was validated through comparison with separate testing and validation sets to detect signs of overfitting. Key performance metrics including Precision, Recall, and Intersection over Union (IoU) were employed to assess the model's predictive capabilities, following evaluation formulas detailed in Eq. (1) to (3) in [15]. This structured methodology ensured that

the YOLOv8 model was effectively trained for high accuracy weed and crop classification tasks.

Figure 1 illustrates the training process of the model using the YOLOv8 architecture across 3 out of 100 epochs, whereas Figure 2 presents a comprehensive visual summary of the model's training performance over the entire run.

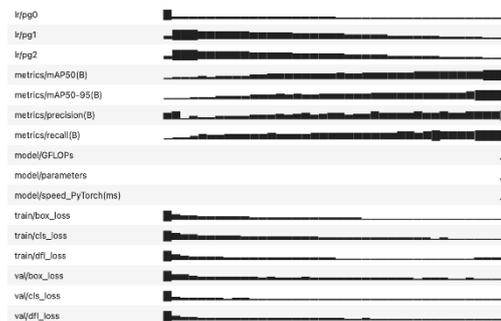Figure 1 Model training progression using the YOLOv8 framework across 3 out of 100 epochs.

Figure 2 Full progression of training metrics throughout the model's learning phases.

The flowchart in Figure 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.
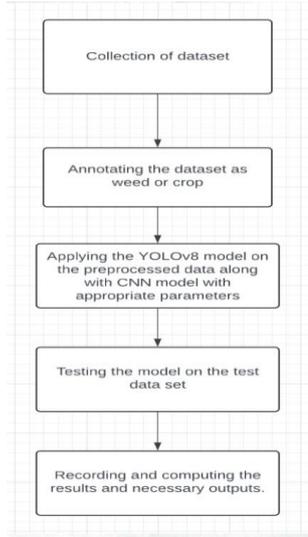
Figure 3 Sequential pipeline illustrating the training and evaluation stages of the YOLOv8 object detection framework.

Figure 4 Classification between weeds and crops (label '0' denotes crops, while label '1' represents weeds)

4.   Results

The YOLOv8 model was effectively deployed using the selected dataset, resulting in a successful classification workflow. This confirms the model's proper construction, training, and validation. As illustrated in Figure 4, the distinction between crops and weeds is clearly established, where class label '0' corresponds to crops and '1' to weeds. Figure 5 presents the precision-confidence curve across varying threshold levels, offering insights into the model's precision stability. It is observed that higher precision is obtained at various confidence levels on the training and testing data (plant and weed). The graph demonstrates that the model achieves excellent precision in detecting both crops (plant) and weed at increasing confidence levels. It is also observed that at the higher confidence levels, the precision value is 1 which indicates a flawless precision score. It demonstrates the effective performance of the YOLOv8 model in distinguishing between crops and weeds in the given dataset [16].

Meanwhile, Figure 6 illustrates the recall-confidence relationship, highlighting recall performance relative to confidence values. It is observed that the recall values decreases as the confidence level increases. This is typical as the model will predict many positives (including both true and false positives) when the threshold is low [16]. The "mean" curves indicates for overall datasets, "plant" and "weed" curves are for testing crops and weed classes, respectively, while "train" curves are illustrated based on training datasets as shown in Figure 5 and Figure 6. Comprehensive evaluation metrics summarized in Table 1 validate the robustness of the classification process. The high precision, F1-score and mAP-50 values show the potential of YOLOv8 in detecting weeds on the images.
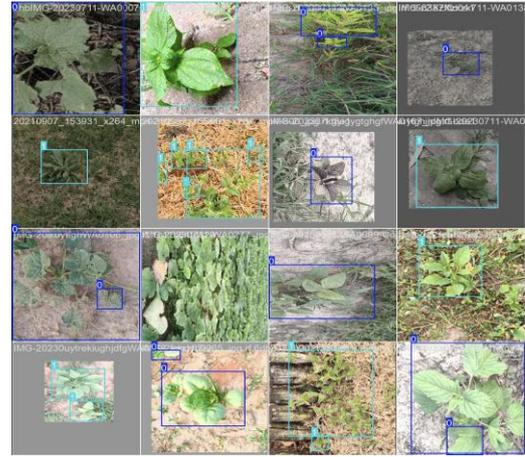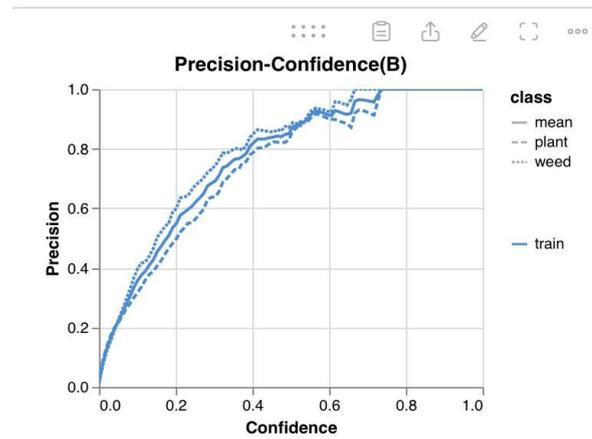

Figure 5 Precision values across varying confidence score thresholds.
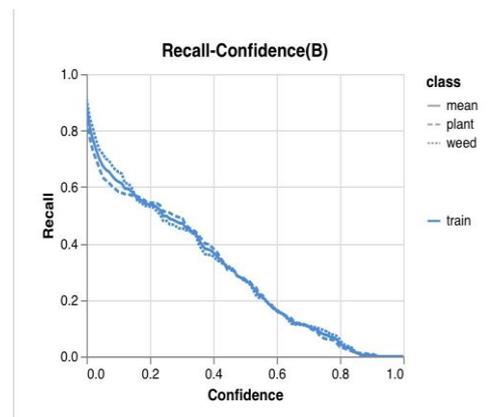

Figure 6 Recall values across a spectrum of confidence thresholds

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Table 1 Collective values of all the metrics taken for the classification.

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

5. Conclusion

In this paper, the effectiveness of YOLOv8 on the given weed dataset was assessed, presenting a more efficient and less resource-demanding alternative with a notable accuracy rate of 0.9895. This degree of accuracy is noteworthy and indicates successful classification. The graphical representation of precision in relation to confidence illustrates that precision nearly reaches its maximum when plotted against confidence at varying thresholds, showing significant improvement at each level. Therefore, it can be concluded that the YOLOv8 model discussed excels at differentiating between weeds and crops, making it a valuable tool for the preliminary stage of weed classification and detection. In the future, datasets should be created that include weeds and crops in various seasons and environmental conditions to enhance the resilience of the model. Furthermore, a range of illumination, scaling and rotations will be applied to the images to diversify the dataset. This can be accomplished by utilizing advanced generative models, such as diffusion models or Generative Adversarial Networks (GANs), to produce high-quality synthetic images of weeds with a variety of backgrounds and scenarios [17].

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