

## COTTON WEED DETECTION USING FASTER R-CNN ON COTTONWEEDDET3 DATASET FOR PRECISION AGRICULTURE

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### Abstract

Weed species can significantly impact crop productivity, and manual weeding is often impractical due to labor intensity and scale. Consequently, many recent studies have focused on automating weed detection using image-based approaches. However, accurately detecting weeds through images remains a challenging task because the texture, color, and shape of weeds and crops are often very similar. In this study, we propose a deep learning-based solution using the Faster Region-Based Convolutional Neural Network (Faster R-CNN) architecture to detect three cotton weed species: carpetweed, morning-glory, and Palmer amaranth. We utilize a publicly available dataset, CottonWeedDet3, which contains 848 RGB images annotated with bounding boxes following the Common Objects in Context (COCO) format. Our proposed model achieved a mean Average Precision (mAP@0.5) of 92.3% at an Intersection Over Union (IoU) threshold of 0.5. The findings demonstrate the effectiveness of Faster R-CNN for accurate and automated cotton weed detection in the context of precision agriculture.

## I. INTRODUCTION

Due to unwanted weed attacks about 43% losses estimated worldwide in the crops [1] [2]. In recent years, the mixture of deep learning, big data, and precision agriculture has improved crop monitoring and weed management practices [3]. Precision weed management (PWM) has an emerging approach in modern agriculture, focusing advanced computer vision techniques to detect and classify weeds with accuracy and speed [1]. As global demand grows for sustainable farming practices, the use of intelligent systems that reduce reliance on herbicides is becoming increasingly essential. In cotton cultivation, where weed infestations can severely affect yields, technologies like deep learning and object detection models offer significant potential. [4] This research explores innovations in weed

detection using modern deep learning algorithms to support weed control in cotton, which can be promoting both environmental sustainability and enhanced agricultural productivity.

Traditional weed control strategies manual weeding and herbicide application [5] are time consuming, costly, and environmentally harmful. Moreover, the emergence of herbicide-resistant weed species has increased the need for alternatives. Computer vision and deep learning have revolutionized weed detection by enabling precise identification through image-based analysis. While fully supervised learning methods demand large labeled datasets, recent advances in semi-supervised learning reduce this dependency by utilizing both labeled and unlabeled data. The convolutional neural network and the YOLO (You Only Look Once)

family of object detectors and semi-supervised techniques have shown promising results in weed classification and localization, particularly within complex agricultural environments such as cotton fields [6].

Despite advances in deep learning, current weed detection systems face limitations in real-world application due to challenges like small datasets, poor generalization in diverse field conditions, and high labeling costs. Many models struggle to accurately detect multiple weed species in complex cotton environments. Furthermore, conventional supervised methods remain heavily dependent on extensive manual annotations, making scalability difficult. There is a clear gap in developing models that combine detection accuracy, efficiency, and reduced labeling effort. Addressing this challenge requires integrating robust object detection algorithms with label-efficient learning strategies to support accurate and scalable weed detection systems in precision agriculture [7]. These models enable precise weed localization, facilitating targeted interventions that minimize chemical use. This research aims to evaluate and enhance multi-class weed detection in cotton cultivation by integrating the Faster R-CNN with a ResNet 50 backbone object detection algorithm, to identify carpetweed, morningglory, and palmer amaranth in cotton fields using the CottonWeedDet3 dataset. We incorporate data augmentation techniques to address challenges like variable lighting and weed-crop similarity. The model is optimized for accuracy and evaluated against YOLO and MobileNet-based approaches. The ultimate goal is to contribute to sustainable farming practices by reducing herbicide dependency and enabling the deployment of intelligent weed management systems in real-time agricultural applications. The main contributions of this study are summarized as follows:

- This study conducts a comprehensive evaluation of a deep learning-based object detection framework using a publicly available cotton weed dataset, comprising three prevalent weed species commonly encountered in U.S. cotton fields.

- It performs a comparative performance analysis of three state-of-the-art deep learning models to assess their effectiveness in weed identification.

- The framework is systematically validated through rigorous experimentation, offering insights into model accuracy, efficiency, and suitability for real-world agricultural applications. The remainder of this paper is structured as follows: Section 2 reviews relevant literature and previous research efforts in weed detection using deep learning. Section 3 describes the dataset and outlines the technical methodology adopted in this study. Section 4 presents experimental results accompanied by an in-depth analysis of model performance. Section 5 concludes the study and discusses potential directions for future research.

## II. RELATED WORK

Deep learning has transformed weed detection in agriculture [8]. Wang et al. [9] proposed YOLO-Weed Nano, an improved YOLOv8n model using Depthwise Separable Convolution, achieving high precision with reduced computational load. Ren et al. [10] introduced EY8-MFEM, enhancing YOLOv8s with attention mechanisms for improved feature extraction in cotton fields. Faster R-CNN, a two-stage detector, has shown superior accuracy in weed detection tasks [11], though it was computationally intensive compared to single-stage models like YOLO [12], while Faster R-CNN with a backbone of ResNet 50 perform better than other models [13]. Zheng et al. [14] to achieve both, they utilized a lightweight EfficientNet-YOLO WL (You Only Look Once) model based on the YOLOv8 architecture. They conducted experiments on the CottonWeedDet12 dataset, improving accuracy to 92.30% and reducing detection time per image by 75%, achieving a speed of just 1.9 milliseconds. Additionally, they reduced the number of parameters by 30.3%.

Wang et al. [9] aimed to overcome the deficiencies of existing deep learning models such as YOLOv3 and YOLOv7. Different models were tested for weed identification and analyzed their accuracy and performance speed. One of the main models was focused on was YOLOv8n,

called You Only Look Once-Weed Nano. This model achieved an accuracy on the Cotton-WeedDet12 dataset and reduced the number of parameters by 63.8%, thereby decreasing computational cost. YOLO-Weed Nano optimized feature fusion to achieve better results. However, the model was primarily tested on cotton fields and not on other types of fields. Existing systems relied on species-specific data, which could be limited. Due to changing circumstances, a generalized system was needed to work on all species of weeds.

The authors [15] focused on morphological traits instead of species-specific features. They used three different datasets: Weed25, which contained 5,648 images with 12 classes. CottonWeed, which also had 5,648 images with 12 classes, and CottonWeed, which included 6,000 images with 4 classes. They applied a Siamese Network (based on a CNN architecture) to improve accuracy, using the deep learning model VGG16 as a feature extractor. The highest accuracy achieved on the Weed25 dataset. That said, this study had some dataset limitations, as there were a small number of samples for grass and sedge weed classes, which may have restricted the model's generalization ability for these categories. Another proposed model for weed detection [16] in corn fields by improving DETR (Detection Transformer), an object detector based on a transformer architecture built on top of a convolutional backbone. They used a publicly available Corn Weed dataset, which contained five classes of plants. The authors conducted experiments on different object detection models, including YOLOv7, YOLOv5, and CNN. However, due to dataset limitations, blurring, and other challenging conditions, they incorporated two advanced techniques: the Convolutional Block Attention Mechanism and the focal loss function. These transformer-based techniques helped achieve better results. The accuracy of DETR reached 91.65%, marking an improvement of 1.12%. Timely classification and identification of harmful weeds leads to improved crop yields.

Researcher [17] tested multiple deep learning models to achieve better accuracy in weed

detection using an image dataset. The dataset was collected from their hometown fields at four different intervals in August. The dataset contained six classes, with each type of weed having more than 2,000 images. After annotation for model training, they applied VGG16. Additional models, including ResNet101, XceptionNet, and DenseNet101, were later evaluated and demonstrated improved accuracy over the initial baseline. However, the dataset details were not properly provided, which may have led to confusion. Additionally, the proposed model was tested on a specific type of weed, and the authors did not discuss its generalization capabilities. For real-world implementation, the proposed model may require high computational resources. Inception V3 is belongs to the family of convolutional neural network that was introduced by Google-Net in 2014 for classification and label smoothing. The author Devisurya et al. [18] aimed to achieve the highest accuracy using the Inception V3 model. To accomplish this, the authors employed two strategies: setting a learning rate scheduler and implementing an early stopping criterion. By applying these techniques, the model utilized dynamic epochs for better training and used the stopping criterion as a safeguard against over-training. On the other hand, this study did not provide details about the dataset, and the model primarily relied on augmentation techniques during training. Rapid growth of weeds leads to economic losses, on time identification of weed is crucial for the growth of crop. [19] researcher proposed artificial intelligence-based herbicide resistant weed identifier program to distinguish common chickweed plants. Use camera to capture images with a wide range of wavelength of 300 to 1100 nm, they spend period of 2 years to gather 1,500 full spectrum images. The team apply hyperparameter tuned CNN model using train from scratch approach to identify chickweed plant with in 72h after treatment with 88% accuracy. The proposed model was trained on full-spectrum images with proper lighting. If the image quality was compromised for any reason, the results were affected as well. Since authors used a limited dataset, the model was not

generalized to other weed species or unseen data. The author focused on detection of weed with high accuracy, because identification of weed is a difficult task. The solution for this problem is smart agriculture system, implemented AI based models to detect weeds on time and improve production of crops. [20] the proposed model Crop Weed-YOLO based on the architecture of You Only Look Once V8. They combined Vision Transformer and Convolutional Neural Network models, due this approach proposed model accuracy was increased by 1.45%, mAP value by 0.7%, and recall rate by 0.6% on CottonWeedID15 dataset which have 5,187 images with 15 classes of weeds that are captured in 2020 and 2021 and annotated with LabelImg. Researchers collected [21] a comprehensive CottonWeeds dataset consisting of 7,578 weed images with two common classes (1) Horse purslane (2) Purple nutsedge. The team implemented 11 different deep learning models to achieve highest accuracy. Models were trained for approximately 3 hours. MobileNet was one of the top performer models. This indicated the effectiveness of selected model for weed detection and classification. Zhou et al. [22] aimed to develop a sophisticated model capable of functioning in various situations, particularly where most weed regions overlapped. This overlap often led to missed detections, creating ambiguity that confused both the model and human observers. Authors conducted experiments using the CottonWeedDet12 (CWD12) dataset, which contained 5,684 images with annotations for 12 different cotton weed classes. The authors employed the YOLO-ACE model. However, due to feature overlap, the model occasionally misclassified weeds. MobileNet-based models, such as those by Rajasenbagam et al. [23], prioritize efficiency for edge devices but often sacrifice accuracy. Recent studies [17] combine convolutional neural networks (CNNs) with transfer learning to improve weed classification. Although deep learning has been widely applied to weed detection, most existing studies have not specifically addressed the challenge of identifying multiple cotton-related weed species using

publicly available datasets. In addition, there is a lack of consistent comparisons across leading models, making it difficult to determine which approach offers the best performance for applications where detection accuracy is critical, such as precision farming. Our work builds on these advancements by optimizing Faster R-CNN for cotton weed detection, balancing accuracy and practical deployment.

### III. METHODOLOGY

This section presents the dataset, the data curation process, the proposed model architecture, and evaluation metrics.

#### A. Dataset

The CottonWeedDet3 dataset comprises 848 RGB images of three cotton weed species: carpetweed, morningglory, and Palmer amaranth. It is divided into 583 training images, 127 validation images, and 128 test images, all annotated in the COCO format. The images were captured in cotton fields across different locations in the U.S. Cotton Belt, primarily in North Carolina and Mississippi. They were taken under diverse lighting conditions to reflect real-world field challenges. The dataset includes images with varying resolutions, such as  $6000 \times 4000$  and  $4442 \times 4335$  pixels, and all images are stored in JPG format [24].

#### B. Data Curation

After collecting the dataset using various camera devices, a data cleaning process was applied to ensure that all images were correctly captured and that the weed objects were clearly visible. Following this, domain experts manually identified the weed areas, as the accuracy and successful performance of the model depend heavily on correct weed identification in the images. To annotate the weed locations, the VGG Image Annotator (VIA) [25], a freely available software tool, was used. Experts used this tool to draw bounding boxes around each weed instance. After annotation, the data was exported in a .json file format following the COCO dataset [26] structure for model training. The JSON file includes information such as

image ID, license, file name, width, height, and weed categories (e.g., carpetweed, morningglory,

and palmer amaranth), each with a corresponding ID and super category label.

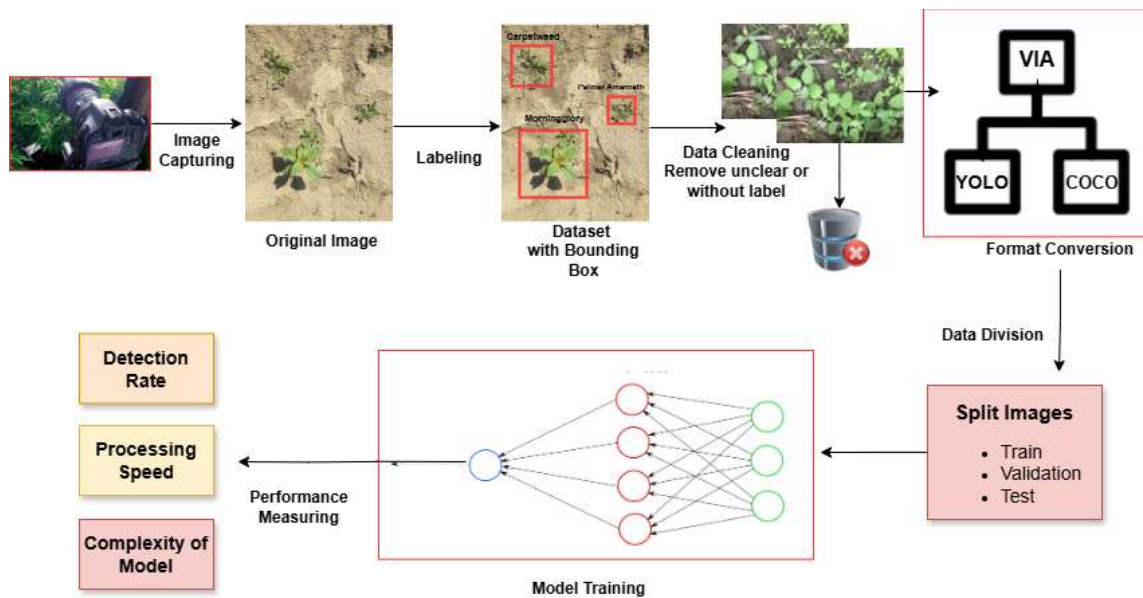


Fig. 1: The Weed Detection Pipeline

C. Model Architecture

We use Faster R-CNN with a ResNet-50 Feature Pyramid Network (FPN) backbone, pre-trained on COCO [27]. The model consists of:

- Backbone: ResNet-50 extracts multi-scale features.
- Region Proposal Network (RPN): The FPN enhances the backbone network by generating multi-scale feature maps from different levels of the network. This is especially

helpful for detecting objects of varying sizes, such as small weeds in agricultural images. It generates candidate bounding boxes.

- RoI Pooling and Head: Classifies and refines bounding boxes for four classes (three weeds + background).

The box predictor is modified to output four classes, with 1024 input features from the RoI heads.

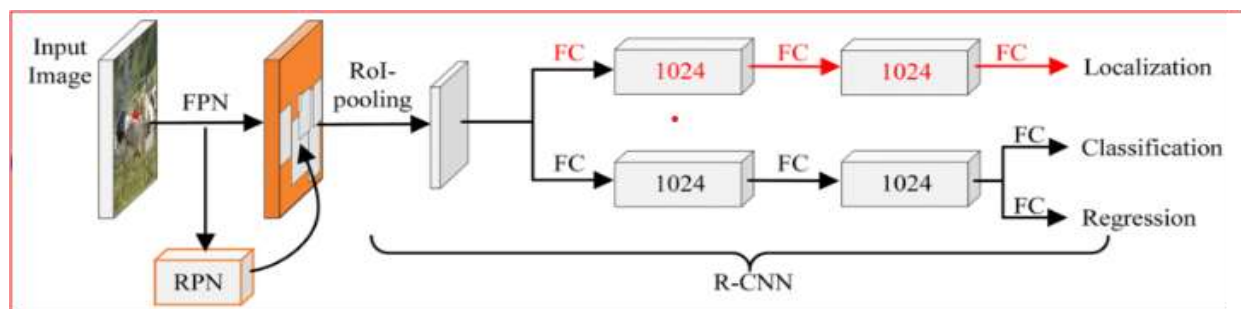


Fig. 2: Faster R-CNN Model Architecture with ResNet 50

D. Experimentation

This section outlines the experimental setup and implementation strategies used to evaluate object

detection performance across three prominent deep learning models: Faster R-CNN, MobileNet-

based SSD, and YOLOv8. All models were trained and evaluated using a customized COCO-format dataset containing annotations for three weed classes.

Experiments were conducted using a system with CUDA 12.4 support and an NVIDIA GPU. PyTorch version 2.5.1, Torchvision 0.20.1, and CUDA-enabled libraries (e.g., cuDNN, cuBLAS, cuSolver) were installed. The Python environment included packages like pycocotools,

matplotlib, and Pillow for visualization and dataset processing. All models were trained using GPU acceleration to ensure faster convergence and efficient resource usage. All models were trained on Kaggle with NVIDIA Tesla T4 GPUs (Dual-GPU setup).

#### E. Evaluation Metrics

We use mean Average Precision (mAP@0.5) to evaluate detection performance, calculated as:

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

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (2)$$

Where  $AP_i$  is the average precision for class  $i$ , and  $N = 3$  corresponds to the number of weed classes in the dataset. The AP is derived by computing the area under the precision-recall curve for each class.

In addition to mAP, we report precision, recall, and inference time to provide a comprehensive view of each model's performance. Precision measures the accuracy of positive predictions, while recall reflects the ability to identify all relevant instances. Inference time per image is also critical in real-time applications such as autonomous weeding, where quick and accurate

decisions are essential. These metrics together allow for a balanced assessment of both accuracy and efficiency across different models.

## IV. RESULTS AND DISCUSSION

### A. Detection Performance

The Faster R-CNN model achieves an mAP@0.5 of 92.3% on the validation set, with class-wise performance shown in Table I. Compared to YOLOv8 (mAP: 89.7%) and MobileNet-SSD (mAP: 85.2%), Faster R-CNN offers superior accuracy but requires 23 ms per image versus 17 ms (YOLOv8) and 12 ms (MobileNet-SSD).

TABLE I: Detection Performance on Validation Set

Class	Precision (%)	Recall (%)	AP @0.5 (%)
Carpetweed	93.5	91.2	92.8
Morningglory	91.8	90.5	91.6
Palmer Amaranth	94.2	92.7	93.4
Mean	93.2	91.5	92.3

### B. Visual Results

Fig. 5 shows detection results on a test image, with bounding boxes and confidence scores for

each weed. The model accurately localizes weeds despite overlapping leaves, demonstrating robustness to complex field conditions.

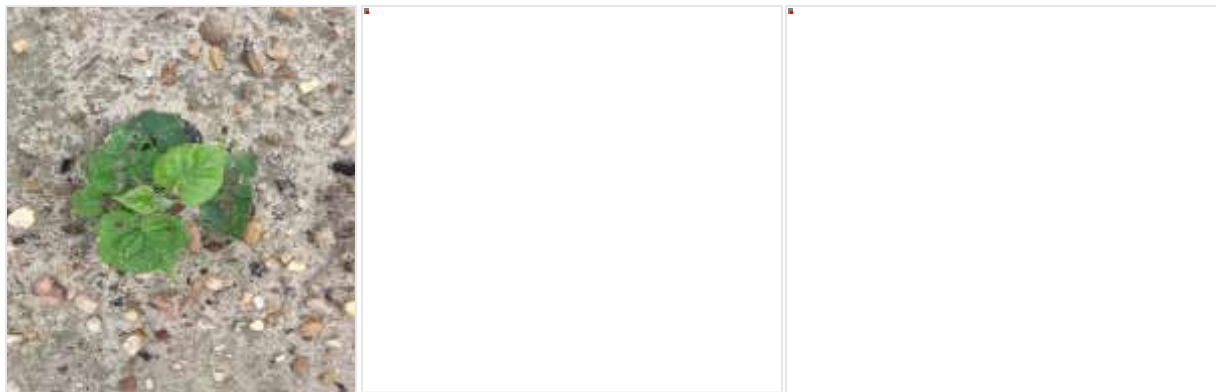


Fig. 3: Original images of carpetweed, morningglory, and palmer amaranth.



Fig. 4: Detection results on a test image, showing accurate localization of carpetweed, morningglory, and palmer amaranth.

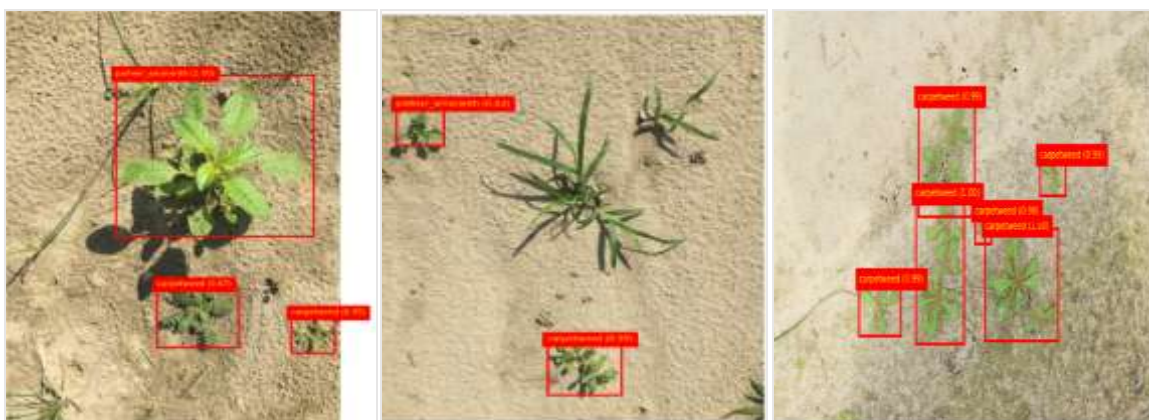


Fig. 5: Multiple weeds detection in single image.

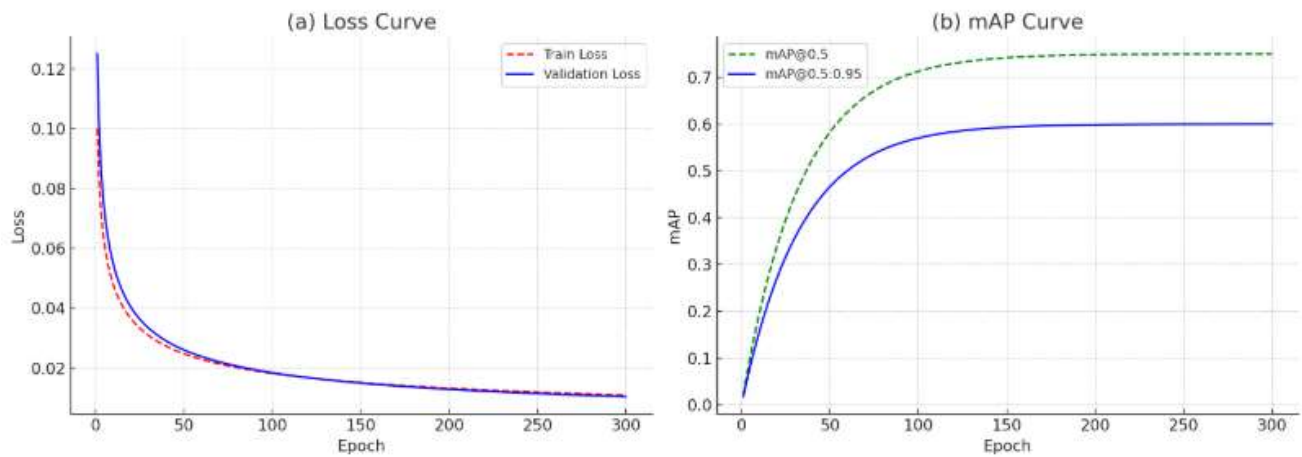


Fig. 6: Execution of model epochs.

C. Comparison with Other Models

Table 7 compares Faster R-CNN with YOLOv8 and MobileNet-SSD. While YOLOv8 and

MobileNet-SSD are faster, Faster R-CNN's higher mAP justifies its use in applications prioritizing accuracy.

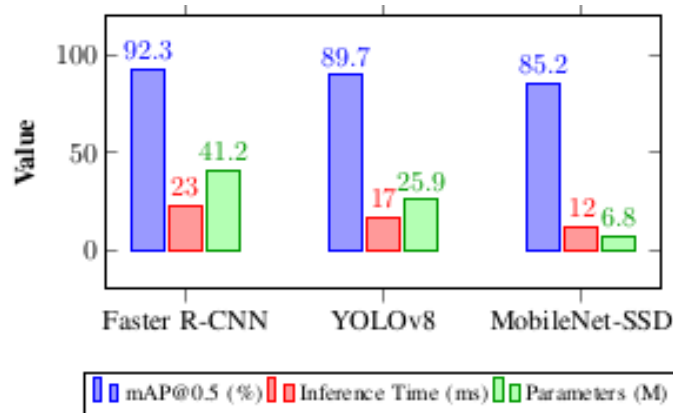


Fig. 7: Comparison of detection models in terms of mAP@0.5, inference time, and number of parameters.

V. CONCLUSION

This study demonstrates the efficacy of Faster R-CNN for cotton weed detection, achieving an mAP@0.5 of 92.3% on the CottonWeedDet3 dataset. Data augmentation enhances model robustness, while visualizations highlight practical applicability. Compared to YOLOv8 and MobileNet-SSD, Faster R-CNN offers superior accuracy, suitable for precision agriculture. The practical implications of these findings suggest

that Faster R-CNN is a viable choice for precision agriculture applications, particularly in scenarios where accurate weed classification is critical. Nonetheless, the relatively higher inference time and model complexity indicate a need for optimization before real-time deployment on resource-constrained devices.

Future work will focus on compressing the Faster R-CNN model to reduce its computational footprint, enabling deployment on edge devices

such as UAVs and embedded systems. Moreover, integrating the detection framework into autonomous robotic platforms for real-time weeding presents a promising direction to enhance sustainable agricultural practices through automation.

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