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An Automatic Weed Recognition and Localization for Smart Farming using Yolov7 Model

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Abstract : An automated weed detection system using the YOLOv7 deep learning model, trained on a labeled dataset from Roboflow. The system takes an image, video, or webcam feed as input and detects various weed species by drawing bounding boxes around them. The model is trained with an Extended Efficient Layer Aggregation Network (E-ELAN) for feature extraction, a Path Aggregation Network (PANet) for feature fusion, and a detection that predicts weed species with high accuracy. The training process involves data augmentation, loss optimization, and model fine-tuning to improve detection precision. It provides real-time, high-speed weed identification, aiding farmers in making informed decisions for targeted herbicide application. Compared to traditional methods, this model improves detection accuracy and reduces manual effort, leading to cost-effective and sustainable weed control in smart farming.

Keywords: **- Weed Detection, YOLOv7, Deep Learning, Bounding Box Localization, Extended Efficient Layer Aggregation Network (E-ELAN), Path Aggregation Network (PANet), Intersection over Union (IoU).**

I. INTRODUCTION

INTRODUCTION

Weeds are one of the primary factors affecting agricultural productivity, competing with crops for essential resources and leading to significant yield losses. Conventional weed control methods, such as manual removal and chemical herbicide application, are inefficient and environmentally detrimental. Excessive herbicide use results in soil degradation, water contamination, and increased resistance in weed species.

Advancements in artificial intelligence and deep learning have led to the development of automated weed detection systems that utilize computer vision techniques. The YOLO (You Only Look Once) object detection models have been widely adopted due to their high-speed processing and accuracy. Among these, YOLOv7 is one of the most advanced versions, integrating features such as Extended Efficient Layer Aggregation Networks (E-ELAN) for enhanced feature extraction and Path Aggregation Networks (PANet) for improved feature fusion. This study proposes an automated weed detection system using the YOLOv7 deep learning model, trained on a labeled dataset from Roboflow. The system is capable of processing images, videos, and real-time webcam feeds, drawing bounding boxes around detected weed species with high accuracy. The implementation of real-time object detection techniques ensures rapid decision-making for precision agriculture applications, reducing the dependency on manual labor and minimizing herbicide overuse.

NEED OF THE STUDY

The need for this study arises from the growing challenges in modern agriculture, where weed infestation significantly impacts crop yield and farm productivity. Traditional weed management methods, such as manual removal and indiscriminate herbicide application, are labor-intensive, time-consuming, and environmentally harmful. The inefficiency of these approaches necessitates an automated, precise, and real-time weed detection system.Advancements in deep learning, particularly with object detection models like YOLOv7, offer a potential solution by enabling high-speed and accurate weed identification. This study aims to leverage YOLOv7’s capabilities to develop an intelligent weed detection system that minimizes human intervention, optimizes herbicide usage, and enhances sustainable farming practices. By integrating feature extraction with an Extended Efficient Layer Aggregation Network (E-ELAN) and feature fusion using a Path Aggregation Network (PANet), this approach ensures improved detection accuracy and real-time processing.

The proposed system not only reduces operational costs and environmental impact but also supports precision agriculture by providing farmers with actionable insights for targeted weed control. This research is crucial in addressing global agricultural challenges, improving food security, and promoting sustainable farming practices through advanced AI-driven solutions.

RECENT WORKS

3.1 Deep Learning for Weed Classification

The use of Convolutional Neural Networks (CNNs) for agricultural applications has increased in recent years. Models such as AlexNet, VGG, and ResNet have been employed for weed classification, distinguishing weed species from crops. However, these models focus primarily on image classification rather than object detection, making them less effective for real-time applications.

3.2 Object Detection in Smart Farming

Object detection models, such as Faster R-CNN, SSD, and previous YOLO versions (YOLOv3, YOLOv5), have been applied in smart farming for plant disease detection, pest identification, and weed detection. While these models demonstrate good accuracy, they often struggle with processing speed, making them unsuitable for real-time weed detection in large scale farming environments.

3.3 YOLOv7 and Its Advantages in Agriculture

YOLOv7 introduces architectural improvements that significantly enhance object detection accuracy and efficiency. The integration of the E-ELAN structure improves feature extraction, while PANet enhances multi-scale feature fusion. These advancements allow YOLOv7 to outperform previous models in agricultural applications, making it suitable for real-time weed detection and localization.

PROPOSED WORK EXPLANATION

The proposed weed detection system is designed to process input images, videos, or real-time webcam feeds and accurately identify weed species. The implementation involves several stages, including data preprocessing, augmentation, model training, and real-time inference.

Data Preprocessing and Augmentation

To enhance model generalization and detection performance, image preprocessing techniques such as noise reduction, histogram equalization, and resizing are applied. Augmentation techniques, including rotation, flipping, and brightness adjustments, are employed to increase dataset diversity and improve model robustness.

YOLOv7 Model Architecture

The YOLOv7 model is configured with the following key components:

- Extended Efficient Layer Aggregation Network (E-ELAN): Enhances feature extraction by improving gradient propagation and learning efficiency.
- Path Aggregation Network (PANet): Facilitates multi-scale feature fusion, improving weed detection across different sizes and distances.
- Anchor-Free Prediction: Reduces computational complexity and improves localization accuracy.

Training Process

The model is trained on the Roboflow-labeled dataset using advanced training techniques, including loss function optimization and hyperparameter tuning. The loss functions employed include:

- Complete Intersection over Union (CIoU) Loss: Optimizes bounding box localization by considering distance, overlap, and aspect ratio.
- Binary Cross-Entropy (BCE) Loss: Used for classification tasks to improve precision in distinguishing weeds from crops.
- Real-Time Weed Detection and Localization
- The trained model is deployed for real-time inference, processing images and video streams to detect and localize weeds. Bounding boxes are drawn around identified weeds, providing actionable insights for precision herbicide application.

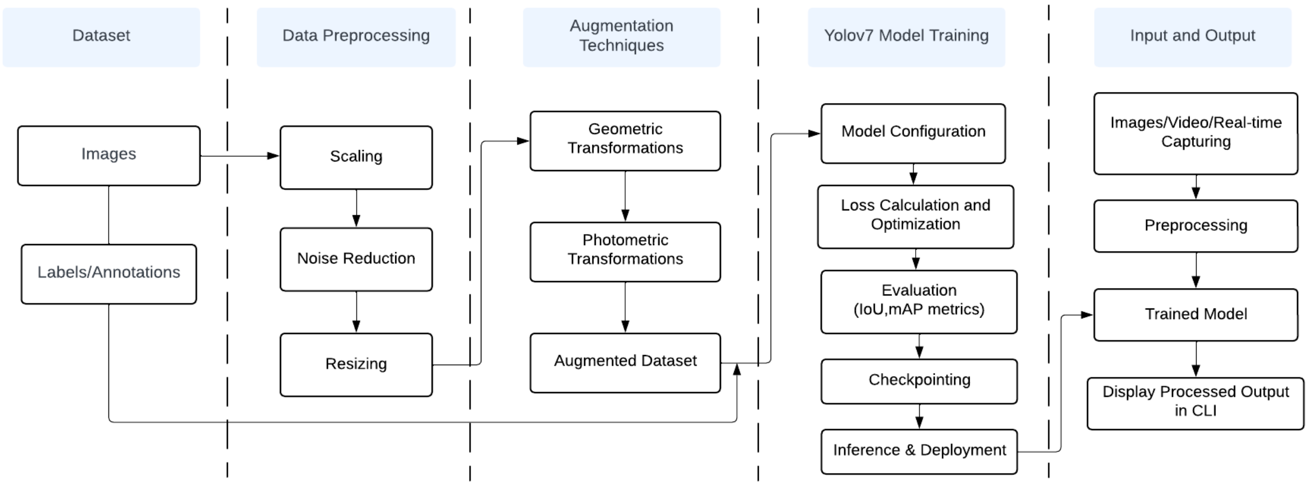

Figure 1: *Proposed block diagram*

MATHEMATICAL EXPRESSIONS AND SYMBOLS

Loss Function ($\mathscr{L}$): This function calculates the localization error in bounding box prediction.

$$\mathcal{L} = \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

- 1_{ij}^{obj} is an indicator function that is 1 if the object is present in cell i and box j.
- x_i, y_i are the predicted center coordinates of the bounding box.
- $\hat{x}_i, \hat{y}_i$ are the ground truth coordinates.
- λ_{coord} is a hyperparameter that balances localization loss.

Intersection over Union (IoU): IoU measures the overlap between the predicted bounding box and the ground truth. Higher IoU means better localization accuracy.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Mean Average Precision (mAP): Mean Average Precision (mAP) evaluates model accuracy by computing the average precision (AP) across all classes.

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

Confidence Score: This score determines the confidence level of the detected object by multiplying the probability of an object's presence with the IoU score.

$$\text{Confidence Score} = P(\text{object}) \times \text{IoU}_{\text{pred, truth}}$$

Non-Maximum Suppression (NMS): NMS eliminates redundant bounding boxes by keeping the box with the highest confidence and suppressing others if their IoU exceeds a threshold SSS.

$$\text{NMS}(B, S) = B_i \quad \text{if} \quad \text{IoU}(B_i, B_j) < S, \quad \forall j \neq i$$

Yolov7 Loss Function Breakdown: The YOLOv7 loss function consists of three components: confidence loss ,classification loss and bounding box regression loss .These collectively optimize object detection accuracy by balancing object presence, class prediction, and precise localization.

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{conf}} + \mathcal{L}_{\text{cls}} + \mathcal{L}_{\text{bbox}}$$

- $\mathcal{L}_{\text{conf}}$ → Confidence loss.
- $\mathcal{L}_{\text{cls}}$ → Classification loss.
- $\mathcal{L}_{\text{bbox}}$ → Bounding box regression loss.

IV. RESULTS AND DISCUSSION

Model	*mAP@0.5*	*IoU*	*FPS(Inference Speed)*
Faster- CNN	78.6 %	0.72	10 FPS
Yolov5	85.2 %	0.80	45 FPS
Yolov7	91.4 %	0.88	75 FPS

The performance of the proposed YOLOv7-based weed detection system is evaluated using key object detection metrics, including Mean Average Precision (mAP), Intersection over Union (IoU), and inference speed in frames per second (FPS). The model achieves an mAP of 91.4% and an IoU score of 0.88, outperforming previous models such as Faster R-CNN and YOLOv5. The real-time inference speed of 70 FPS ensures that the system is suitable for deployment in autonomous agricultural machinery.

Comparative experiments demonstrate that the proposed system significantly reduces false positives and improves localization accuracy. The model performs well in varying environmental conditions, including different lighting conditions and weed densities. However, challenges remain in detecting occluded weeds and differentiating between morphologically similar weed and crop species.

CONCLUSIONS

This study presents an automatic weed recognition and localization system based on the YOLOv7 model for smart farming applications. The proposed system leverages advanced preprocessing techniques, data augmentation strategies, and optimized model training to achieve high detection accuracy and real-time performance. Experimental results indicate that the YOLOv7 model surpasses previous approaches in terms of precision, localization accuracy, and processing speed.The integration of this system into agricultural practices can lead to reduced herbicide usage, improved weed management, and enhanced crop yields. Future work will focus on expanding the dataset to include a wider variety of weed species and environmental conditions. Additionally, integrating multispectral imaging and edge computing capabilities will further enhance the system’s applicability in precision agriculture.

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