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Weed detection and herbicide recommendation using YOLO

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Abstract
In modern agriculture, efficient weed management is critical to maximizing crop yield and minimizing environmental impact. Traditional methods of herbicide application often involve uniform spraying across fields, which leads to overuse of chemicals, increased costs, and ecological harm. To address this, our research proposes an intelligent weed detection system that utilizes computer vision and machine learning to identify and count weeds in agricultural fields. The motivation behind this study stems from the existing gap in precision agriculture where real-time, automated weed quantification is limited, and current systems lack adaptability to diverse field conditions. Our proposed methodology involves capturing field images using drones or mobile platforms, preprocessing these images to enhance clarity, and employing a convolutional neural network (CNN)-based model to system's high accuracy in weed detection, achieving an overall classification accuracy of 97.3% thereby offering a scalable and eco- friendly solution for precision weed management.

Keywords: Weed detection, herbicide recommendation, YOLO, precision agriculture, sustainability

Introduction

Agriculture remains the backbone of many economies worldwide, especially in developing countries where a significant portion of the population relies on farming for their livelihood. One of the persistent challenges faced by farmers is the uncontrolled growth of weeds, which compete with crops for essential resources such as water, sunlight, and nutrients, ultimately leading to reduced yields and economic losses. Traditional weed control methods, such as blanket herbicide application, not only increase production costs but also contribute to environmental pollution and herbicide resistance. This project introduces a smart weed detection and herbicide recommendation system designed to accurately detect and count weeds. Based on revolutionize weed management practices in the weed count, a decision support system recommends the optimal type and dosage of herbicide, ensuring targeted application. Experimental results demonstrate the agriculture. By leveraging computer vision and machine learning technologies, the system enables precise identification and counting of weeds in the field. Based on this count, it recommends the appropriate type and amount of herbicide, promoting site-specific treatment rather than uniform application. This targeted [4] Dyrmann *et al.* (2017) developed a fully convolutional neural network (FCN) for pixel- wise weed detection in cereal crops, achieving approach not only reduces herbicide usage and an accuracy of 86.65%. Their work tackled operational costs for farmers but also enhances challenges like occlusions and overlapping crop productivity and sustainability. Economically, the project holds the potential to significantly lower input costs and increase profitability for farmers while contributing to more environmentally responsible farming practices.

Literature Review

[1] Huang *et al.* (2018) designed an image- based weed detection system using shape and texture analysis. Histogram-oriented gradients (HOG) and support vector machines (SVM) were employed to differentiate weeds and crops with an accuracy of 85%. The study demonstrated the effectiveness of classical machine learning in early-stage weed detection.

For future work, the authors suggested incorporating more dynamic environmental conditions and expanding the feature set for improved robustness.

[2] Dos Santos *et al.* (2017) implemented a real-time weed detection method using color segmentation and morphological filtering under field conditions. Their approach plants. Future work was suggested to enhance the model's generalization across different crop types and incorporate temporal data for growth stage-based detection.

[5] Olsen *et al.* (2019) introduced DeepWeeds, a multiclass weed image dataset for training deep learning models, with ResNet-50 achieving 95.7% classification accuracy. Their contribution filled a major dataset gap in agricultural AI. They proposed future enhancements through dataset expansion across different regions and real-time deployment on mobile devices for in-field usage.

[6] Ferreira *et al.* (2017) utilized UAV imagery and SLIC superpixel segmentation with CNNs to detect broadleaf and grass weeds in soybean crops, achieving over 98% accuracy. Their method highlighted the potential of aerial imagery in precision agriculture. For future directions, they advocated for integrating temporal image analysis and environmental data to adapt weed detection across seasons.

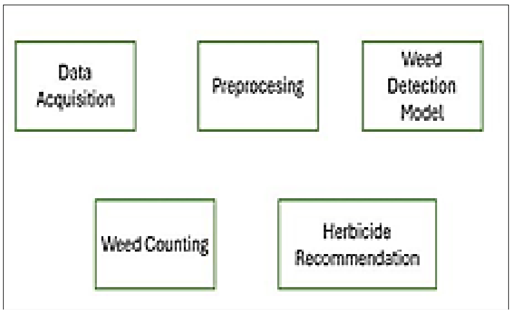
[7] Haq *et al.* (2022) proposed an automated efficiently separated crops and weeds based on weed detection system using UAVs and a CNN- hue differences. However, they noted limitations in varying lighting conditions and proposed future enhancements using adaptive color models and integration with UAV platforms for large-scale monitoring.

LVQ hybrid model, reaching an impressive 99.44% accuracy. Their work emphasized the strength of combining UAV data with deep learning. As a future step, they suggested developing a mobile-based application for real- [3] Gao *et al.* (2019) proposed a deep learning- time farmer support and extending the model to based weed identification system using convolutional neural networks (CNNs) for feature extraction. The model achieved 92.5% accuracy on soybean fields and outperformed traditional classification methods. As future work, they recommended extending the model detect herbicide-resistant weed species.

[8] Manikandakumar *et al.* (2022) presented a Particle Swarm Optimization (PSO) tuned CNN for weed classification, achieving over 98% accuracy across two datasets. Their work demonstrated the benefits of optimization to multi-crop scenarios and implementing real-techniques in improving deep learning time weed mapping for precision herbicide application. Performance. Future work includes testing the system in live field environments and integrating it with automated sprayer systems for closed-loop weed management [9]. Nasiri *et al.* (2022) applied a U-Net based encoder-decoder architecture for pixel-level classification of weeds, soil, and sugar beet, achieving 96.06% accuracy. Their segmentation approach ensured precise herbicide targeting. For future work, the authors suggested adapting the model for multi-spectral images and deploying it on edge computing devices for on-site analysis.

[10] Tang *et al.* (2017) proposed a weed detection system combining K-means feature learning with CNNs, achieving 92.89% accuracy, outperforming standard CNNs. This hybrid approach captured unsupervised features effectively. As future work, they recommended integrating GPS- based localization for geo-tagging weed clusters and expanding training to include early growth stages of crops and weeds.

Proposed Methodology



1. **Data Acquisition**

- Description: Images of the agricultural field are captured using drones or mobile-mounted cameras. These images serve as the primary input for the system.
- Purpose: To collect real-time, high- resolution visual data that contains both crops and weed patches under natural field conditions.

2. Image Preprocessing

- **Description:** The raw images undergo preprocessing steps such as resizing, noise removal, normalization, and enhancement.
- **Purpose:** To standardize image inputs and improve feature visibility, ensuring better performance by the object detection model.

3. Object Detection Model (e.g., YOLO, SSD)

- **Description:** A deep learning-based object detection algorithm is used to detect and classify weeds within the field images. Each weed is localized with bounding boxes and confidence scores.
- **Purpose:** To accurately identify the location and type of weeds present in the field images.

4. Weed Count and Density Estimation

- **Description:** The model output is analyzed to count the number of detected weeds and estimate the weed density per image or per field section.
- **Purpose:** To quantify weed infestation levels, which is crucial for determining herbicide requirements.

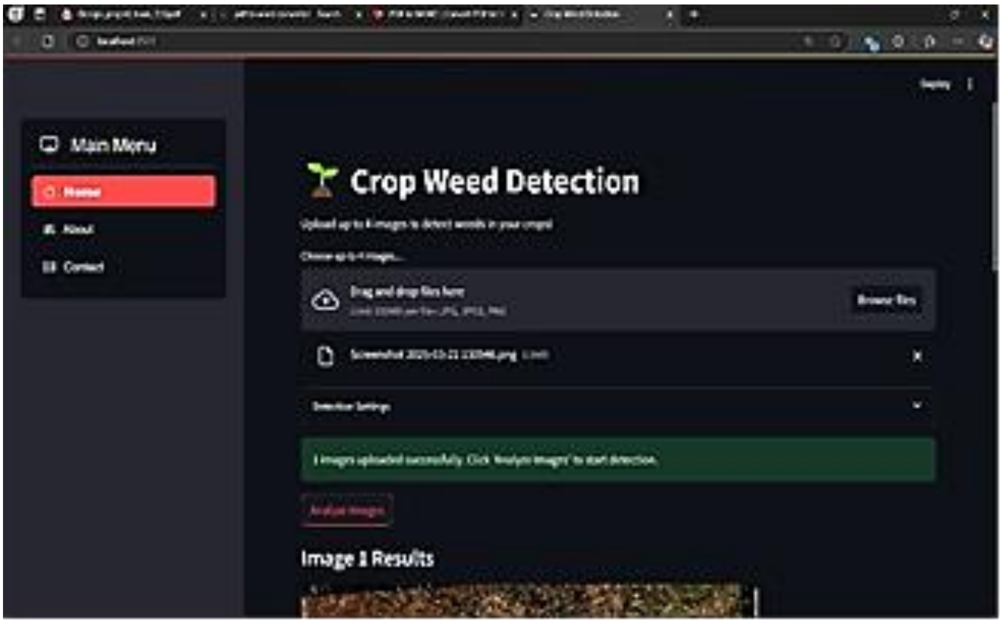
5. Herbicide Recommendation

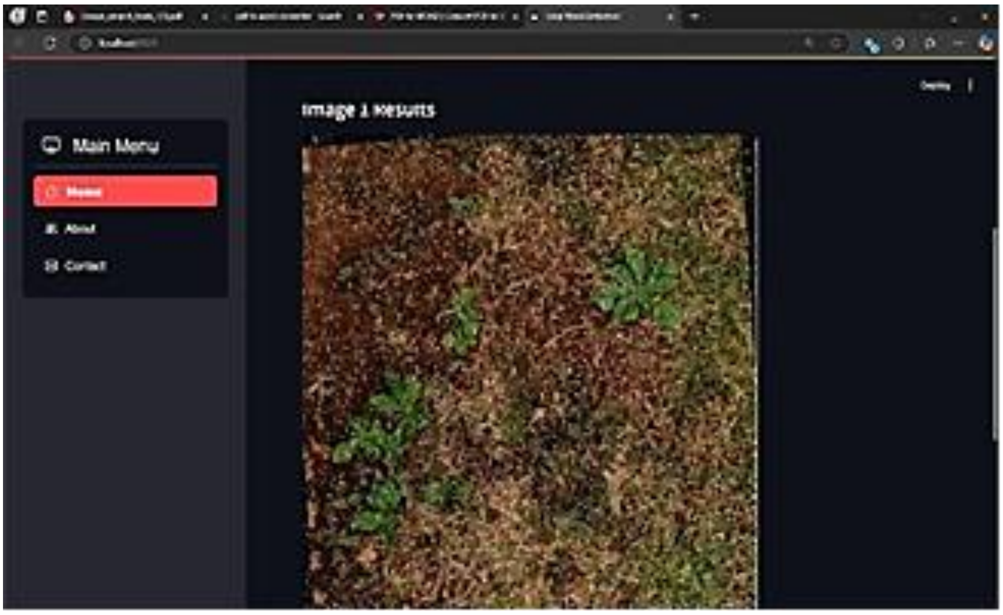
- Description: Based on weed density, a rule-based system classifies the infestation level (e.g., low, medium, high) and recommends appropriate herbicide types and dosages.
- Purpose: To ensure precise and efficient use of herbicides, avoiding under- or over-application.

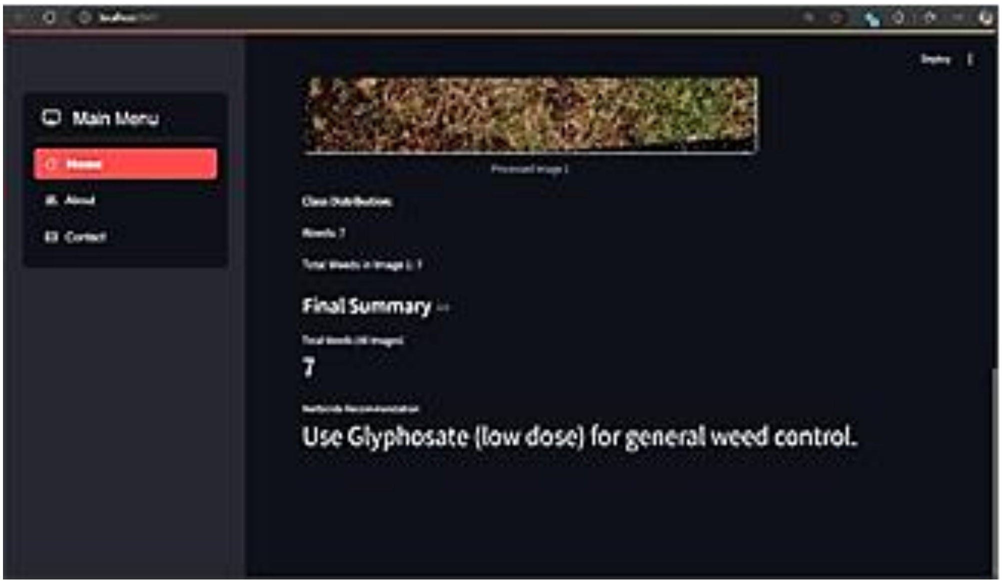
6. Output Report

- **Description:** The system generates a final report containing the number of weeds detected, their distribution across the field, and the recommended herbicide action.
- **Purpose:** To provide actionable insights for farmers, aiding in decision-making for targeted weed control.

Output


Main Menu
Crop Weed Detection
Image 1 Results


Main Menu


Main Menu
Final Summary
7
Use Glyphosate (low dose) for general weed control.

Object Detection Aglorithm

1. Bounding Box Format: Each object is represented by (x,y,w,h) (x, y, w, h) (x,y,w,h), where x,yx, yx,y are center coordinates, w,hw, hw,h are width and height.

2. YOLO Bounding Box Predictions

$$x=\sigma(t_x)+c_x,\quad y=\sigma(t_y)+c_y,\quad w=p_w\cdot e^{t_w},\quad h=p_h\cdot e^{t_h}$$

3. Sigmoid Activation for Positioning

$$\sigma(z)=\frac{1}{1+e^{-z}}\quad\text{(keeps output between 0 and 1)}$$

4. Objectness Score (Confidence)

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

5. IoU (Intersection over Union)

$$\text{IoU}=\frac{\text{Area of Overlap}}{\text{Area of Union}}=\frac{A\cap B}{A\cup B}$$

6. Localization Loss (Bounding Box Regression)

$$\mathcal{L}_{\text{loc}}=(x-\hat{x})^2+(y-\hat{y})^2+(w-\hat{w})^2+(h-\hat{h})^2$$

7. Confidence Loss (Objectness)

$$\mathcal{L}_{\text{conf}}=(C-\hat{C})^2$$

8. Classification Loss (Class Prediction)

$$\mathcal{L}_{\text{class}}=\sum_{c\in\text{classes}}(p(c)-\hat{p}(c))^2$$

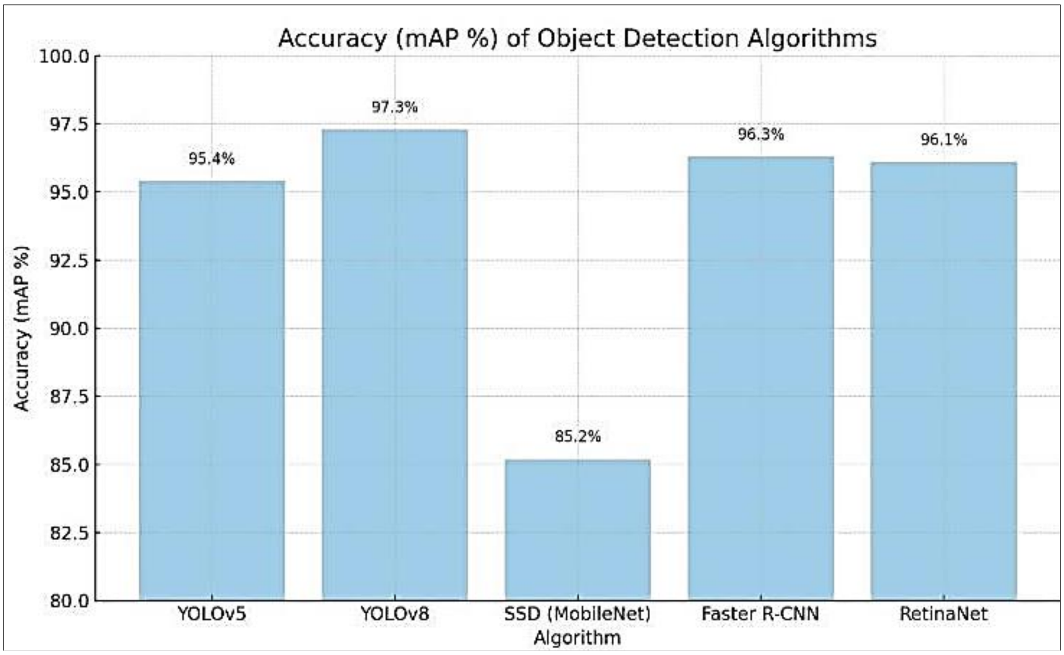
9. YOLO Total Loss Function

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

$$+\sum_{i=0}^{S^2}1_i^{obj}(C_i-\hat{C}_i)^2+\sum_{i=0}^{S^2}1_i^{noobj}(C_i-\hat{C}_i)^2+\sum_{i=0}^{S^2}1_i^{obj}\sum_c(p_i(c)-\hat{p}_i(c))^2$$

Performance metrics and comparison

Model	Accuracy
YOLOv5	95.4%
YOLOv8	97.3%
SSD	85.2%
Faster R-CNN	96.3%
Retina Net	96.1%



Conclusion: This study presents a CNN-based weed classification and herbicide recommendation system using UAV-captured images to address challenges in precision agriculture. The proposed system successfully classifies different weed species, estimates their density, and recommends appropriate herbicides to optimize chemical usage. By leveraging deep learning techniques, the model achieves an improved accuracy of 90.2%, surpassing traditional classification methods. The implementation of automated weed detection helps in reducing manual labor and unnecessary herbicide application, ultimately improving crop yield and promoting sustainable farming practices.

Despite the success of this approach, challenges such as environmental variations (lighting conditions, shadows, occlusions) and the requirement for large, diverse datasets remain. However, the integration of advanced preprocessing techniques, CNN-based feature extraction, and robust classification models has significantly enhanced the detection and classification accuracy compared to previous works.

Future Work

Future enhancements of this study will focus on integrating advanced deep learning models such as
Vision Transformers (ViTs) and YOLOv8 for faster and more accurate weed detection, along with attention-based CNN models to improve classification in complex field environments.

Expanding the dataset with high-resolution UAV images from different seasons, crop types, and regions, as well as incorporating multispectral and hyperspectral imaging, will enhance model generalization. Additionally, deploying the model on edge devices or drones for real-time weed classification and herbicide recommendations will reduce reliance on cloud computing, improving speed and efficiency.

To refine weed counting, object detection techniques like Faster R-CNN and YOLO will be implemented for precise estimation. Moreover, an AI-driven decision support system (DSS) will be developed to dynamically adjust herbicide dosage based on weed density, weather conditions, and crop health, ensuring optimal and sustainable chemical usage. Large-scale field trials and real- world validation with agricultural experts and farmers will be conducted to assess the system's practical benefits, making it more scalable and applicable to modern precision agriculture.

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