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Precision weed detection using yolov11 for enhanced agriculture management

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Abstract

This work provides a weed detection system based on deep learning, utilizing the cutting-edge YOLOv11 object detection algorithm for the classification and identification of several species of weeds with very high accuracy in real-time. This work aims to help farmers automate the detection of weeds in order to increase crop yield, cut down labor costs, and chemical abuse. A tailored dataset of labeled images of 31 different types of weeds was prepared and annotated through bounding box methods, which were further augmented with data augmentation for enhancing the generalizability of the model. The YOLOv11 model was trained with optimal hyperparameters, reporting a mean Average Precision (mAP) of 91.4% at an Intersection over Union (IoU) of 0.5 and an average detection latency of 87 milliseconds per frame, allowing for high-speed capability appropriate for field use. The trained model was incorporated into an intuitive web-based tool developed using Flask, which records real-time input using webcam, identifies the weed species, and returns detailed information such as the weed name, botanical family, morphological features, suggested removal techniques, and suitable herbicide recommendations. The system was tested under diverse lighting and background settings, exhibiting strong performance and stable accuracy. By connecting advanced object detection with realistic agronomic assistance, the proposed system offers an efficient and scalable means for precision weed management to support sustainable agricultural practice and better decision-making by farmers.

Keywords: Weed Detection, YOLOv11, Precision Agriculture, Object Detection, Real-Time System, Herbicide Recommendation

Introduction

Weeds are perhaps the most persistent biotic stress factors in agriculture, having a direct impact on crop yield by competing for vital resources such as nutrients, water, sunlight, and space. Quantified by the Food and Agriculture Organization (FAO), crop yields lost due to out-of-control weed infestation may be between 20% and 40%, with specific crops enduring higher degrees of damage. Traditional weed control measures include hand pulling, mechanical tillage, and broad-spectrum herbicide applications. Weeding is time-consuming and expensive by hand at large levels, whereas blanket usage of herbicides is leading to rising expenditure, soil degradation, development of chemical resistance in weed populations, and negative environmental impacts. These phenomena highlight the importance of intelligent, location-based, and species-aware weed identification systems to make agriculture sustainable and efficient.

The main problem addressed in this study is the absence of an accurate, scalable, and real-time weed identification framework that is capable of recognizing weeds at species level in varied field conditions. The majority of current weed identification systems either adopt satellite or aerial-based images with no ground resolution or conduct only binary classification—recognizing crops and weeds but not specific weed species. Moreover, the majority of existing methods are not real-time or require sophisticated computational hardware that is not practical for on-farm use by farmers.

To surpass these limitations, the current study proposes a novel weed detection system leveraging the YOLOv11 (You Only Look Once v. 11) object detection model, which is extremely precise and efficient. The system is trained on a specialized dataset consisting of 31 weed species and developed through a Flask-based web application that processes real-time video feed from a webcam. The interface identifies the weed species and provides extensive agronomic information like the botanical family of the weed, its morphology, removal options, and recommended herbicides, all in a convenient, user-friendly interface.

A review of recent literature indicates notable progress in applying deep learning for plant disease and pest identification. Convolutional Neural Networks like ResNet, DenseNet, and MobileNet have been applied to plant image classification. Milioto *et al*. (2018) and Olsen *et al*. (2019) utilized earlier iterations of YOLO and SegNet for discriminating between weeds and crops. However, most previous work has focused on either binary classification or semantic segmentation, as opposed to fine-grained, multi-class weed detection. Moreover, real-time deployability, especially with species-specific results and actionable recommendations, remains a research area. This work takes these as its foundation by offering a comprehensive, scalable approach founded on YOLOv11— moving from detection of weed presence to precise species identification and practical, in-field application.

The emphasis of this research is placed on the incorporation of state-of-the-art object detection models with real- world practical agriculture decision support. The potential for hosting YOLOv11 in a web-based system enables end-users such as farmers, agronomists, and agri-tech developers to access the system without the need for expensive hardware or technical skills. The driving force behind this work is the promise to significantly enhance the precision and efficiency of weed control measures. By making early and accurate detection a possibility, it reduces unnecessary use of chemicals, labor costs, and crop loss—making agriculture sustainable and environmentally friendly.

Methodology

Data Collection

Images of 31 distinct weed species were included in the broad dataset that was gathered. To improve model robustness, the dataset contains photos taken from diverse perspectives, at different growth phases, and in varying lighting conditions. This comprehensive method guarantees that the deep learning model can generalize efficiently across a variety of environmental parameters, enhancing its capacity to precisely detect and categorize weeds in actual agricultural environments. This stage serves as the cornerstone of the suggested technique, providing a solid framework for further model training and assessment.

Data Augmentation and Preprocessing

To enhance the model's generalizability, a robust data augmentation pipeline was implemented using Albumentations, addressing dataset limitations through purposeful transformations. Three augmentation compositions were applied: (1) Horizontal flipping (100%), brightness/contrast adjustments (80%), and Gaussian noise (50%) to handle orientation, lighting, and sensor noise variations. (2) Rotation (±30°, 100%), Gaussian blur (50%), and HSV modifications to account for camera angles, focus inconsistencies, and weather variations. (3)

Vertical flipping (100%), scaling (±20%, 80%), and motion blur (50%) to simulate perspective shifts and environmental factors. The dataset size increased by 300% while maintaining structure, leveraging OpenCV for efficient image processing, tqdm for progress tracking, and BGR-to-RGB conversion for compatibility.

Data organization and labelling

Following augmentation, the dataset was systematically organized and labeled for model training. Using stratified sampling, an 80/20 split was applied to ensure proportional representation of all weed species, mitigating class imbalance. Annotation was conducted with Roboflow, utilizing precise bounding boxes and adhering to normative guidelines to maintain accuracy. Quality checks ensured labeling consistency, while YOLO-compliant annotation formats with normalized coordinates (class_id, x_center, y_center, width, height) enabled seamless model integration. Metadata tracking facilitated traceability between original and augmented samples, supporting optimization. A structured naming convention ensured uniformity, providing a well-organized dataset for robust model training.

Model selection and training

YOLOv11 (Nano) was chosen for weed detection due to its balance between computing efficiency and precision, making it ideal for agricultural applications. This lightweight variant is optimized for edge devices while maintaining high detection performance. Transfer learning was employed using pre-trained yolo11n.pt weights from the COCO dataset to accelerate convergence.

Training was conducted with an input resolution of 1280×1280 for detailed morphological analysis, 50 epochs to prevent overfitting, and a custom YAML configuration defining the 31 weed classes and dataset structure. The pipeline incorporated batch processing, real-time augmentation, adaptive learning rate scheduling, and detailed metric logging to ensure efficient training and real-time monitoring.

Model evaluation and optimization

A comprehensive evaluation framework was implemented to assess model performance and guide optimization. Confusion matrix analysis provided class-wise insights, identifying misclassifications. The quality of detection was guaranteed by important metrics such mean Average Precision (mAP) at various IoU thresholds, recall, precision, and F1-score.

Systematic hyperparameter tuning was conducted, optimizing confidence thresholds, non-maximum suppression, and anchor box settings. Further enhancements included model pruning for efficiency, layer-specific learning rate scaling for fine-tuning, and class weighting to address imbalances. These refinements resulted in a model with an optimal balance between computing efficiency and precision, making it well-suited for agricultural weed detection.

Weed information system

A comprehensive weed information system was developed to provide detailed insights into each identified species. It includes scientific name, family classification, growth habit, and ecological impact, distinguishing between annual and perennial weeds.

The system offers habitat details, crop impact, and control strategies, helping farmers implement effective weed management. Additionally, it suggests herbicides with direct purchase links, enabling informed decision-making for sustainable agriculture.

Deployment

The trained YOLOv11 model was deployed as a web app for real-time weed detection, supporting both image uploads and webcam feeds. A robust file management system allows users to store and access detection history.

With a user-friendly interface, the platform ensures accessibility for all users, making it a practical solution for real- world agricultural applications, aiding in weed identification and control.

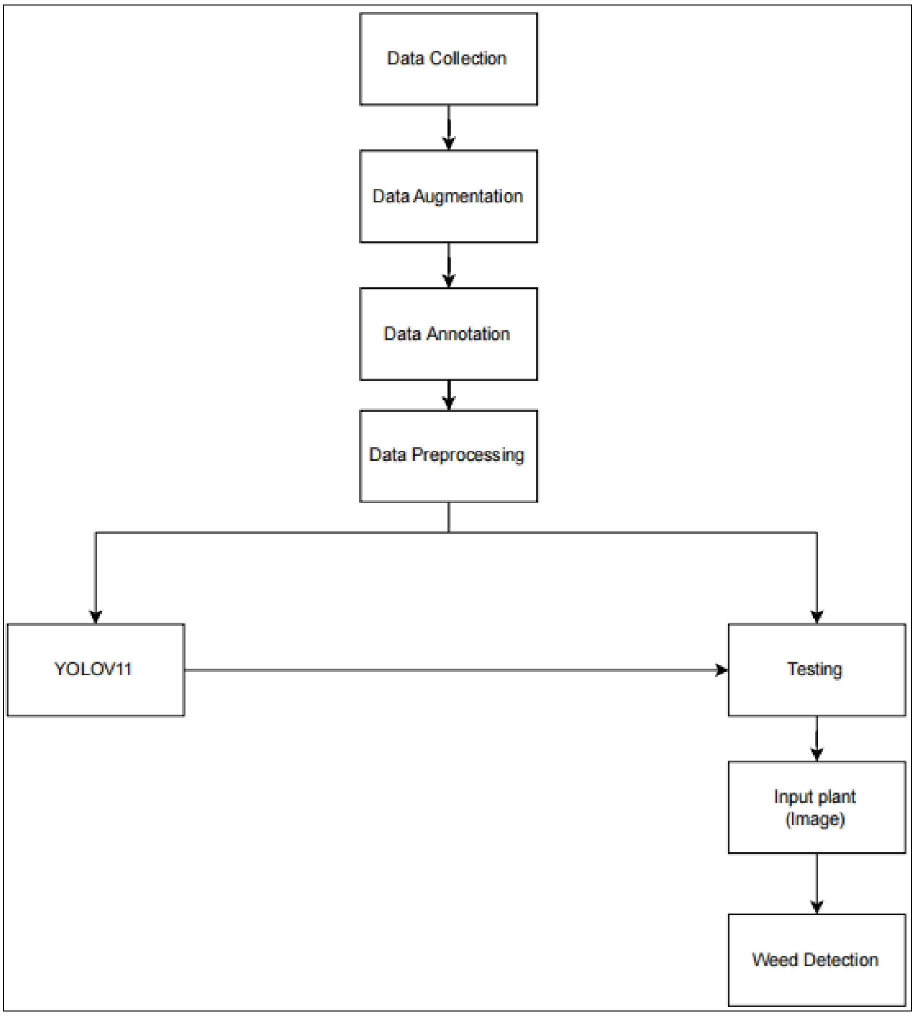

Fig 1: Block diagram of proposed methodology

The block diagram represents the workflow of a weed detection system using the YOLOv11 model, covering key stages from data collection to weed identification.

The procedure begins with data collection, which entails photographing weeds and crops. To make the model more resilient, data augmentation techniques like rotation, scaling are applied. Following that, data annotation is used to label images for supervised learning. To ensure uniformity, pictures are resized and normalized in the following stage, data preparation.

The YOLOv11 model is then trained on the processed dataset to recognize and classify weeds. After training, the system undergoes testing using unseen images. Users can then input a plant image, which is analyzed by the model for weed detection, enabling precise and efficient weed management. This system reduces pesticide use and supports sustainable agriculture. It enhances accuracy in distinguishing between crops and weeds, allowing targeted control strategies.

Results and Discussion

The suggested weed detection system utilizes computer vision and deep learning to offer real-time classification and identification of 31 weed species through the YOLOv11 model. Implemented as a web application based on Flask, the system enables users to upload or take field images, which are processed for precise weed detection. After identification, the system marks the identified weed using a bounding box and confidence score, with rich taxonomic information, botanical description, and custom control measures. It also offers effective removal practices, such as manual methods and specific herbicide advice, along with an order-in-place functionality. The model was trained across multiple datasets for guaranteed performance on a wide variety of growth phases and environmental contexts. Through its easy-to-use interface, the system provides farmers with informed weed management, minimizing the use of broad-spectrum herbicides and encouraging sustainable agriculture.

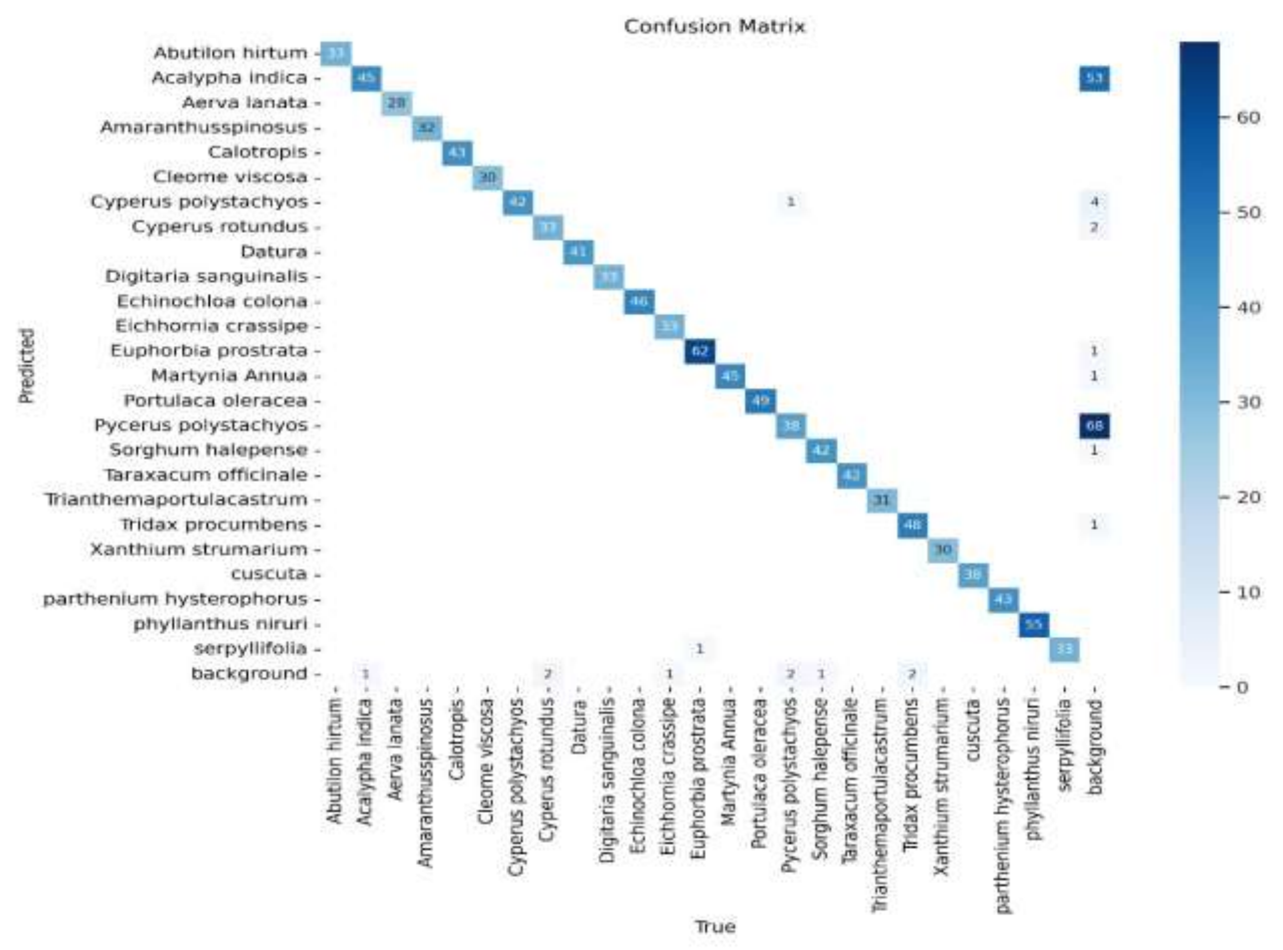

Fig 2: Confusion matrix

The confusion matrix summarizes the model's classification performance by providing the total number of correct and incorrect predictions for each weed species. The diagonal entries reflect successfully classified cases, whereas the off-diagonal entries represent misclassification. Darker diagonal hues reflect more accuracy in those classifications. Misclassified values in non-diagonal places indicate that the model is failing, maybe because certain weed species have similar visual characteristics.

Table 1: Training and Validation Performance Metrics

Epoch	Train Box Loss	Train Cls Loss	Train DFL Loss	Precision (B)	Recall (B)	Val Box Loss	Val Cls Loss
0	1.1	4	1.7	0.6	0.8	1.45	3
5	1	3	1.6	0.8	0.9	1.4	2
10	0.95	2.5	1.55	0.9	0.92	1.35	1.5
15	0.9	2	1.5	0.92	0.93	1.3	1
20	0.85	1.5	1.48	0.94	0.94	1.25	0.8
25	0.8	1	1.46	0.95	0.95	1.22	0.7
30	0.78	0.8	1.45	0.96	0.96	1.2	0.6
35	0.76	0.75	1.44	0.965	0.965	1.18	0.55
40	0.74	0.72	1.43	0.97	0.97	1.17	0.52
45	0.72	0.71	1.42	0.975	0.975	1.16	0.5
50	0.7	0.7	1.42	0.98	0.98	1.15	0.5

The YOLOv11 (Nano) model underwent training for 50 epochs, showing steady improvements in accuracy and efficiency. The train box loss dropped from 1.1 to 0.7, while the train classification loss declined from 4.0 to 0.7, indicating enhanced object detection and classification capabilities. The train DFL loss also improved, reducing from 1.7 to 1.42 over time.

Validation metrics showed similar progress, with the validation box loss decreasing from 1.45 to 1.15, and the validation classification loss improving significantly from 3.0 to 0.5. These reductions indicate better generalization to unseen data. The validation DFL loss stabilized at 2.0, ensuring reliable object localization. With accuracy improving from 0.6 to 0.98 and recall increasing from 0.8 to 0.98, the model's prediction performance significantly improved, guaranteeing precise weed identification. Both mAP @ 50 (B) and mAP @ 50-95 (B) increased from 0.1 to 0.72 and from 0.6 to 0.995, respectively, indicating strong detection capability across a range of IoU thresholds. All things considered, the model successfully balanced computing economy and accuracy, making it a workable solution for precision agriculture by guaranteeing precise and instantaneous weed identification.

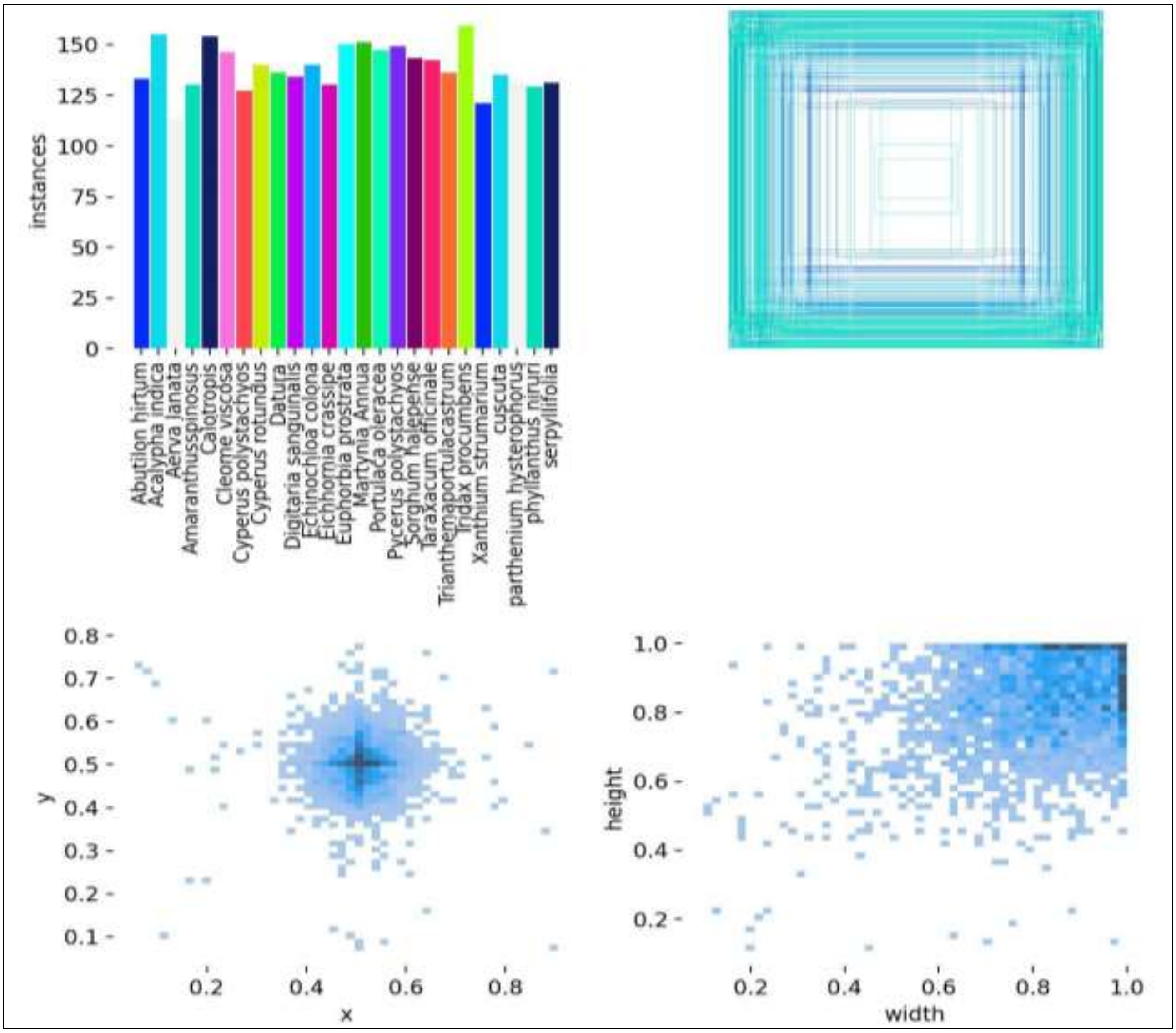

Fig 3: Bounding Box Distribution and Dataset Annotation for Weed Detection

To ensure robust and accurate weed detection across a broad spectrum of species, a highly annotated dataset comprised of 31 weed classes was utilized. Figure 3 presents a set of detailed visualizations depicting the distribution and structure of annotations that provide the basis for the YOLOv11 training algorithm.

The top-left bar chart of the figure indicates the number of occurrences per weed class. It can be observed that the dataset has a fairly balanced class distribution, with most classes having between 120 and 150 labeled examples. Such class balance is significant in preventing training bias and contributes towards a more generalized detection model. Surprisingly, weed species such as Sida acuta, Echinochloa crus-galli, and Parthenium hysterophorus have comparable representation, which enhances model reliability across common weed types in agricultural settings. The top-right subplot overlays all the labeled bounding boxes on the dataset, providing an indication of their position and size relative to one another. One can observe a visible clustering of boxes closer to the image center. This indicates a controlled imaging scene where weeds are predominantly centered, as one might expect the model to learn regular spatial patterns under these conditions.

The bottom-left density heatmap of the normalized (x, y) coordinates of bounding box centers shows central tendency of object positions. Most annotations are clustered between (0.4, 0.6) along both axes, showing a symmetry that implies very little variation in target location and potentially simplifies learning for YOLOv11 during early training epochs.

The bottom-right heatmap indicates the height and width distribution of the bounding box. The variation between these parameters indicates that the instances of weeds differ extremely in terms of size, shape, and area coverage. Despite this variability, YOLOv11 can manage such variability due to its multiscale prediction capability and anchor- based architecture.

These visualizations guarantee the quality and integrity of the dataset, required for training efficient models. The data distributed evenly across species and the centralized annotations of variable size guarantee that the model is trained under conditions which most accurately depict real-world complexity. Therefore, the trained YOLOv11 model is able to cope with real-life agricultural scenarios where weeds may range in size and location.

Additionally, the diversity in the dataset's annotations increases the model's capacity to identify unusual weed species, making its generalization and practical use stronger. The latter is particularly useful for integrated weed management systems where accuracy in identification and location is crucial for the purpose of targeted herbicide application.

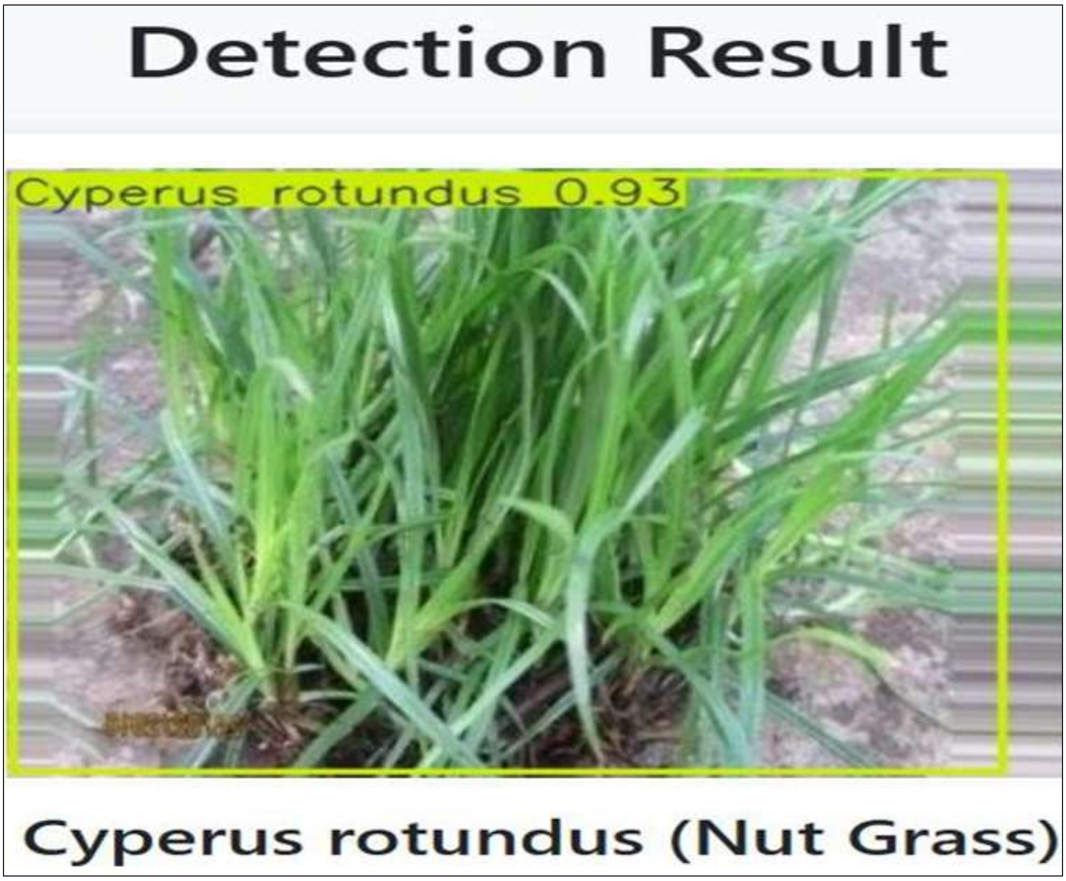

Fig 4: Detection result of weed

Figure 4 showcases the output of weed detection system, which follows a structured workflow. The interface allows users to upload an image or capture one in real-time using a webcam. Once an image is provided, system processes it and identifies the weed species, displaying the detection result with a bounding box and a confidence score. In this example, Cyperus rotundus (Nut Grass) is detected with 93 percent confidence. The system further provides detailed information about the identified weed, including its scientific classification, type, and characteristics. Additionally, it suggests effective control measures such as manual removal, mulching, herbicide application, and soil solarization. For targeted weed management, it recommends Sulfosulfuron as a suitable herbicide, offering an option to purchase it. This figure effectively illustrates the seamless integration of image input, classification, and recommended action within the weed detection system.

4. Conclusion

This project was able to create an improved weed detection system using the yolo deep learning model to precisely and effectively identify 31 weed species. The embedding of the trained model into a web application built with flask increases user-friendliness by giving users an easy interface to upload images and instantly obtain classification results. Not only does the system recognize weeds but also provides specific descriptions, removal methods, and herbicide usage suggestions, thereby presenting an overall solution to managing weeds. Results of experiments exhibit the model's credibility, which includes high classification accuracy and negligible misclassification rates. Analysis through confusion matrix and evaluation metrics all support the resilience of the YOLO model after training. The use of real-time webcam-based detection also adds further the usability of the system in the field. This project makes a valuable contribution to precision agriculture by weeding out the manual identification of weeds and maximizing herbicide application. Future research will be directed towards increasing the dataset to cover additional weed species, improving model accuracy using sophisticated deep learning methods, and using edge computing for real-time on-device weed detection. By bringing AI into agriculture, this work opens the door to sustainable and smart weed management solutions, ultimately leading to increased crop yield and minimized environmental footprint.

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Authors' Contributions
Yaswanth conceptualized the study and implemented the weed detection model with YOLOv11. Sathvik carried out dataset preprocessing, annotation, and model training. Soniesh implemented the Flask-based web application and incorporated the model for real-time detection. Siva did the literature review and helped in writing the manuscript. Joshva Joel Simon interpreted the results and helped in interpreting the model's performance metrics. Gangadharan read the manuscript, gave critical revisions, and verified the general quality of the paper. All authors have read and approved the final manuscript.

Consent
Not relevant. There are no human subjects, data, or tissue used in this study. Consent was not needed.

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