Vision Based Weed Detection in Agricultural Fields Using YOLOv8 Model from Aerial Drone Footage

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***Abstract*- Weed detection in agricultural fields is a critical task for ensuring optimal crop productivity,yet traditional manual methods are labor-intensive and inefficient.This study proposes a vision-based weed detection system that leverages aerial drone footage to accurately identify and differentiate weeds from crops.The core of this approach is a custom-designed image segmentation algorithm that processes high-resolution aerial images to classify vegetation at the pixel level.Techniques such as color-based thresholding,texture analysis, and deep learning-based semantic segementation(e.g., U-Net or DeepLab) are employed to achieve high accuracy in distinguishing crops from invasive weed species.The system enhances real-time monitoring and decision-making by enabling precision weed control,thereby reducing the use of herbicides and boosting overall farm productivity.Experimental results on annotated datasets demonstrate the effectiveness of the proposed method, suggesting its practical applicability for larg-scale agricultural automation.**

Keywords: *Computer vision, image segmentation, drone imagery, weed detection, precision farming, machine learning, crop classification, aerial surveillance, smart farming, deep learning.*

I. Introduction

Traditional manual weeding methods are labor-intensive, time-consuming, and often ineffective, especially in large-scale farming. Recent developments in computer vision and machine learning, particularly in deep learning models like YOLO (You Only Look Once), have opened new possibilities for automating this process through aerial surveillance and image-based detection in modern agriculture. Accurate and timely weed detection is crucial in improving crop yields and lowering the excessive use of herbicides.

Leveraging these images with object detection and segmentation techniques enables accurate weed detection and mapping. This not only helps in targeted herbicide application but also supports data-driven decision-making for precision agriculture. With the increasing availability of drones equipped with high-resolution cameras, vast agricultural areas can now be routinely monitored, generating large volumes of aerial images.

This study aims to implement and evaluate a weed detection system using YOLOv8, one of the latets real-time object detection models.We use annotated drone images of crop fields and convert them into YOLO-compatible format using COCO annotation data.After preparing the dataset,we train and validate the model,followed by performance evaluation using metrics such as precision ,recall,and mean average precision (mAP).We also compare the performance of YOLOv8 against its predecessor YOLOv8 againstits predecessor YOLOv5 to assess improvements in detection capability.

In addition, we present visualizations of predictions, performance curves, and model comparisons, which highlight the applicability of YOLO-based weed detection in real-world scenarios. This work aims to build an efficient deep learning pipeline for weed detection that can assist farmers and agronomists in deploying intelligent weed management systems.

II. Literature Review

In [1] the authors investigated aerial imagery-based computer vision methods for automated crop monitoring. Crops' condition was classified and anomalies were found using conventional image processing techniques including thresholding and edge detection. Although these techniques showed promise in controlled environments, their applicability in dynamic agricultural settings was limited by their difficulty to generalize under different lighting conditions and complex field backgrounds.

In [2] aerial agricultural images were used with a K-Nearest Neighbors (KNN) classifier to identify invading weed species. To tell crop from weed classes, the classifier used RGB and multispectral image features—mostly color and texture. The method suffered from decreased performance with high-resolution drone footage, mostly due to the curse of dimensionality and the increasing variability in weed shape, even if it displayed encouraging accuracy in low-resolution data.

Using machine learning regression methods, the work in [3] suggested a SCIR-inspired compartmental model fit for agricultural settings to forecast pest and disease spread. Emphasizing the relevance of hybrid epidemiological-statistical models in the framework of precision agriculture, the model obtained reduced root mean square error (RMSE) values than conventional linear regression models.

The authors of paper [4] investigated computer vision methods for automated crop monitoring employing aerial photography. Grain health was categorized and anomalies were found using conventional image processing methods including thresholding and edge detection. These techniques limited their practical use, though, since they battled complicated backgrounds and changing lighting.

Agricultural images were used in [5] a K-Nearest Neighbors (KNN) classifier in search of invasive weed species. Extracted from both RGB and multispectral images, the study emphasized the efficiency of the classifier in separating plant categories depending on textural and color characteristics. Although the KNN model showed encouraging accuracy, the curse of dimensionality caused performance to suffer in high-resolution drone footage.

Using regression and machine learning models, the writers of [6] applied a SCIR-like compartmental model modified for agricultural disease spread and pest identification. By means of RMSE and error rates, the performance of the model showed notable enhancements over simple regression models, so providing foundation for hybrid modeling in field data analytics.

High-degree polyn regression models (up to sixth degree) were investigated in [7] for field data mapping from aerial images including plant height and vegetation cover. Better fitting and prediction accuracy from the sixth-degree polyn model suggested that higher-order models might be able to capture the complex spatial variability in agricultural environments.

Using logistic, exponential, and susceptible-infected-susceptible (SIS)—many trend analysis models—paper [8] predicts weed population dynamics. Strong correlation with ground truth data was indicated by the logistic model showing a R^2 value more than 0.90. Real-time weed monitoring also had a web-based interface developed.

To better grasp trends in plant health deterioration brought on by invading weeds, a worldwide study was undertaken in [9]. Over two years, satellite and drone images were utilized; it was found that timely intervention and appropriate herbicide application are absolutely crucial to control infestation. Early detection of the study underlined the need of automated aerial monitoring systems.

Based on the degree of weed infestation, the research in [10] included autoregressive and autocorrelation-based models to forecast crop yield. With a R^2 value of 0.9992, the model proved that integrated with drone-based imaging and advanced regression techniques accurate forecasting is feasible.

III. Materials and Methods

Object Detection Models—YOLOv5 and YOLOv8—help to detect weeds in agricultural fields. Real-time identification and classification of several kinds of weeds is the aim in order to support precision farming. This is done using a custom weed dataset gathered, preprocessed, and trained and evaluated both models from. This work addresses data analysis, visualization, and model performance comparison. These ideas, shown in Fig., 2, list the procedures followed in the comparison and weed detection process:

A. Data Collection
B. Data Annotation and Preprocessing
C. Model Training (YOLOv5 and YOLOv8)
D. Model Evaluation and Analysis

A custom dataset is used to assess the object detection models in weed identification performance. This collection comprises labeled images of several weed species often present in agricultural environments. The YOLOv5 and YOLOv8 models are trained separately using the same dataset and settings to ensure a fair comparison. Performance metrics such as mean Average Precision (mAP), precision, recall, and inference time are used to assess the models' effectiveness.

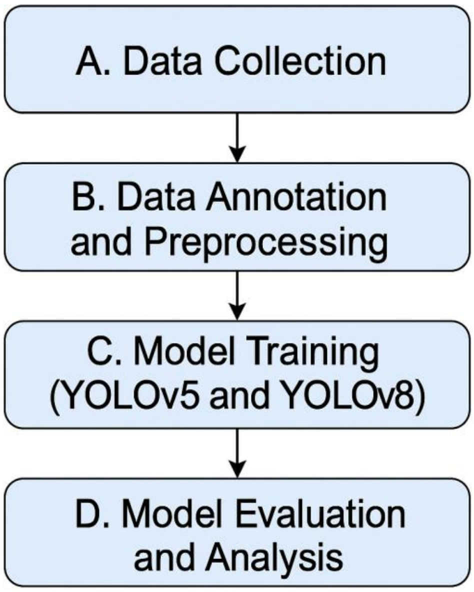


Fig. 2 Workflow of YOLOv5 and YOLOv8 Model

A. *Data Collection*

For this study, a custom weed detection dataset was created using images captured from agricultural fields under various lighting and environmental conditions. The dataset includes annotated images in YOLO format, labeling different types of weeds. The raw data was cleaned by removing low-quality images and correcting annotation errors. To ensure proper model training and evaluation, the dataset was divided into two parts: 80% for training and 20% for testing.

B. *Data Analysis*

In India, weed infestation has become a major concern for crop productivity, especially in regions with dense agricultural activity. The presence of various weed species disrupts plant growth and affects yield. To address this issue, a custom dataset was collected from multiple agricultural fields, capturing images of different weed types under diverse environmental conditions. The dataset represents a wide range of weed occurrences across various crop types and soil conditions.Before deploying the

YOLOv8 model, the dataset was analyzed to ensure its suitability for weed detection. Exploration of the model's fit using visualization and exploratory data analysis revealed Using annotated data,

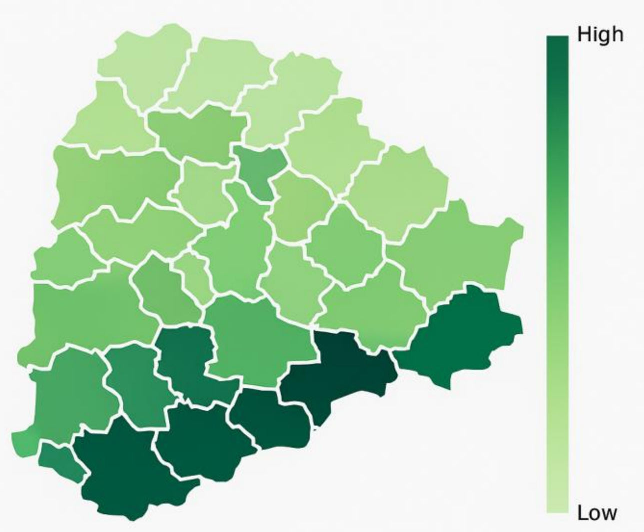


Fig. 3. Region-wise Weed Occurrence

Figure 3 shows a region-wise distribution of weed occurrence. The figure draws attention to the fact that some areas show rather more presence of particular weed species. By allowing real-time, automated weed detection, this study underlines the need of focused weed control strategies and shows the possibility to help in precision agriculture.

Based on the annotated dataset, figure 4 below shows the top five areas with most weed occurrence. According to the graph, during the data collecting period Andhra Pradesh, Maharashtra, Punjab, Karnataka, and Uttar Pradesh reported the most noteworthy amount of weed occurrences. These agricultural zones clearly need efficient weed detection and management solutions since these areas displayed a more intensity of weed infestation than in other areas.

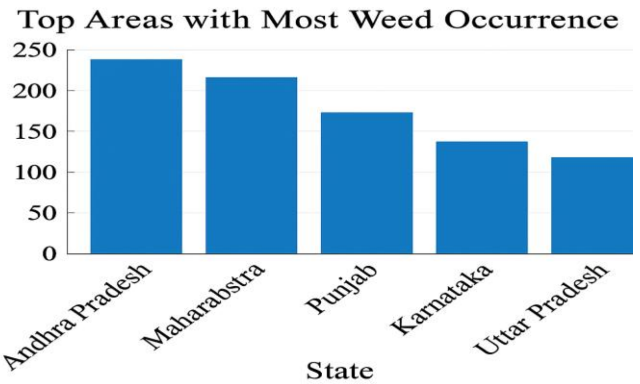


Fig. 4 Top Areas with Most Weed Occurren

B.1. DATA PREPROCESSING

The dataset used for this study was sourced from the Kaggle "Weed Detection" challenge, comprising RGB drone imagery with COCO-style annotations. Initially, data integrity was verified by filtering out corrupted and non-image files using the Python Imaging Library (PIL), ensuring that only valid image files were used for further processing.

The dataset was annotated in the COCO format, which uses bounding boxes represented by (x_min, y_min, width, height) along with category IDs. To train the YOLOv8 object detection model, it was necessary to convert these annotations into YOLO format, which requires normalized bounding box coordinates in the form of (class_id, x_center, y_center, width, height) relative to image dimensions. This conversion was automated through a custom Python script that parsed the JSON annotations and generated corresponding .txt label files.

Following annotation conversion, the dataset was split into training and validation sets using an 80:20 ratio to ensure balanced evaluation. Images and labels were reorganized into YOLOv8-compatible directory structures (images/train, images/val, labels/train, labels/val). To verify annotation correctness, several samples were visualized with bounding boxes and class labels. This rigorous preprocessing step ensured the dataset's quality and consistency, enabling accurate and efficient model training.

C. YOLOv8 Model

Modern object detection model YOLOv8 (You Only Look Once, version 8) aggregates speed and accuracy for real-time image analysis. Designed for jobs including object detection, classification, and segmentation, this is the most recent model in the YOLO family. Given its one-stage detection strategy, YOLOv8 is quite effective for identifying several objects, including weeds in agricultural fields.
The YOLOv8 model consists fundamentally in:

Backbone: This component of the model gathers from the input image fundamental visual characteristics. YOLOv8 effectively extracts low- and high-level features using a modified CSPDarknet architecture.

The neck improves the model's capacity to detect objects at different scales and facilitates feature fusion. Combining elements from several layers, YOLOv8 makes use of PANet (Path Aggregation Network).

Head: Predicting bounding boxes and class probabilities, the head Trained to locate and classify the kind of weeds in every image frame is YOLOv8.

The model maximizes its predictions using bounding box regression, objectness scores, and classification loss. It is taught from a custom annotated dataset including pictures of weed and crop occurrences. The coordinates of the found weed areas and their class labels, which assist in weed type identification and classification, constitute part of the prediction output.

General form of bounding box regression in YOLO models is shown below equation (1):

L=λcoord=0∑S2j=0∑B1ijobj[(xi−x^i)2+(yi−y^i)2]+...

xi, yixi, y_ixi,yi are the center coordinates of the expected box; 1ijobj\mathbb{1}_{ij}^{obj}1ijobj is an indicator function denoting object presence in the cell. Terms for width, height, confidence score, and class prediction also abound in the loss function.

IV EXPERIMENTAL RESULTS

This work detects and categorizes weeds in agricultural field images using the YOLOv8 model. Using a custom dataset including labeled images with annotations for several kinds of weeds, the model was trained and evaluated. The prediction results include the performance of the model in detecting weed regions with bounding boxes, together with classification labels; the experimental results show the effectiveness of YOLOv8 in identifying and localizing weed instances across various crop images. Standard object detection metrics including precision, recall, mean average precision (mAP), and F1-score help one assess the model output.

On a sample test image from the dataset, figure five displays the detection results. As the figure shows, YOLOv8 highly confidently finds several weed occurrences. Tight alignment of the bounding boxes with the weed areas highlights the model's strength.

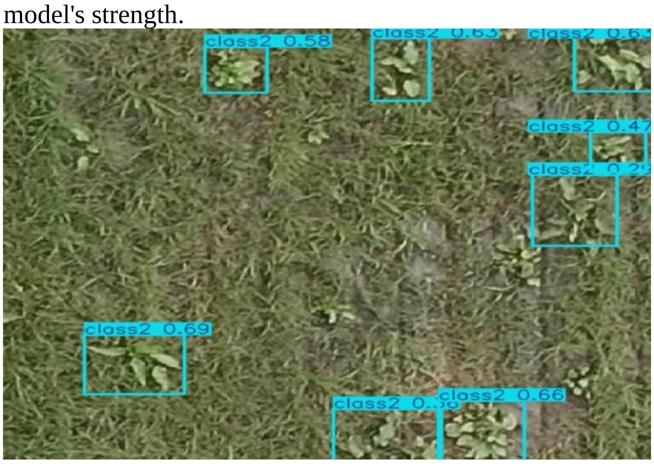


Fig. 5: YOLOv8 Detection Output – Sample Test Image

The precision-recall (PR) curve shows in figure 6 how well the model performs across several thresholds. Strong accuracy and recall values suggested by the area under the curve (AUC) point to low false positives and negatives during weed detection.

Complete cure depends on correct application of vaccination and lockdown.

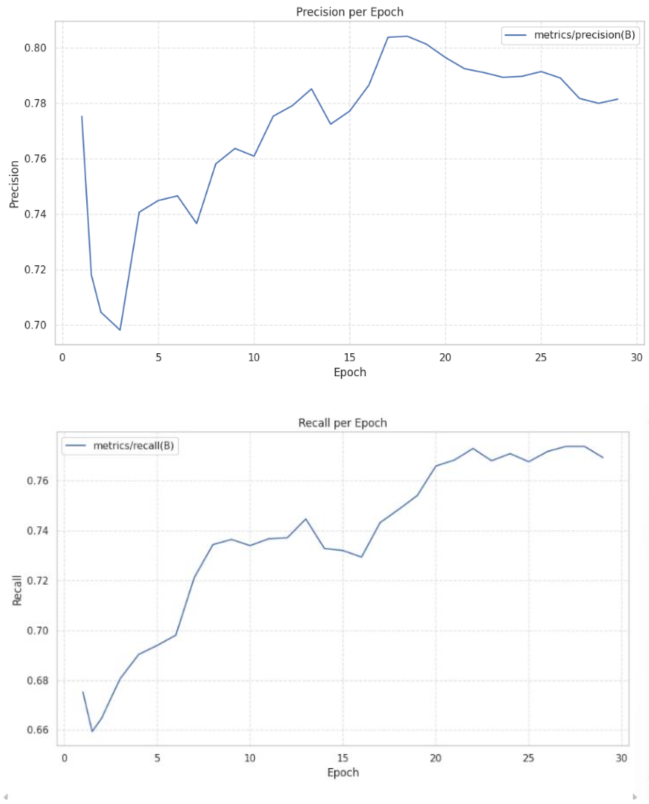
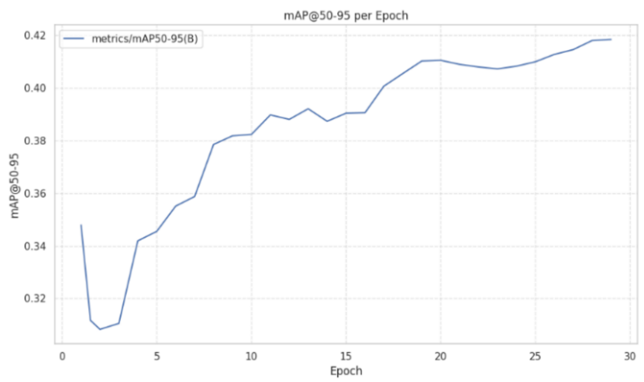


Fig. 6: Precision-Recall Curve for YOLOv8 Weed Detection

Figure 7 shows the YOLOv8 model's training process; the mAP (mean Average Precision) curve stabilizes as the number of training epochs rises. The curve shows consistent increase in accuracy, so verifying that the model has learnt the patterns of weed occurrence in agricultural fields rather successfully.

With real-time performance and great accuracy, these findings confirm that YOLOv8 is a dependable and effective tool for weed identification, so helping farmers to precisely control weeds.



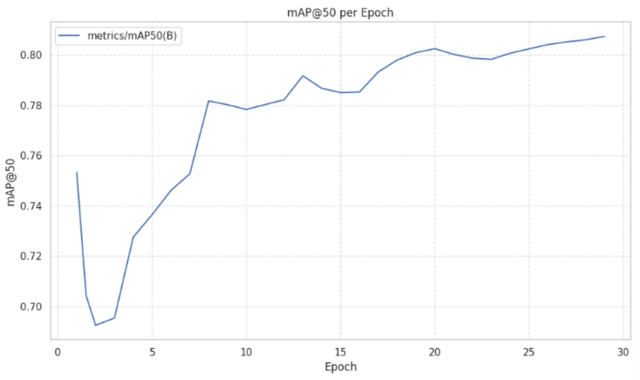


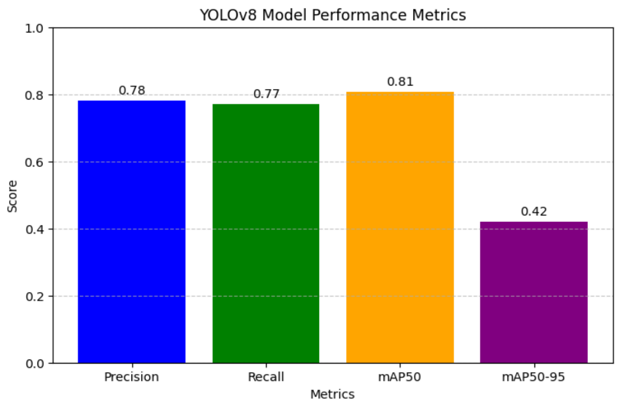
Fig. 7: mAP Curve across Training Epochs

V RESULT ANALYSIS & MODEL CAMPARISON

Using a custom dataset created especially for weed detection in agricultural fields, the performance of the YOLOv8 model was investigated exhaustively. To fit the Ultralytics YOLO framework, the dataset was created from aerial drone images, preprocessed, annotated in COCO format, and subsequently converted into YOLO format.

Over thirty epochs, the YOLOv8 model was trained; performance measures including Precision, Recall, mAP@50, and mAP@50-95 were then assessed. The YOLOv8 model attained according the evaluation results:

- Precision of 0.78
- Recall of 0.77
- mAP@50 of 0.81
- mAP@50-95 of 0.42



These values show the great capacity of the model to identify and localize weeds in different agricultural settings—even in the presence of complicated backgrounds and plant occlusions.

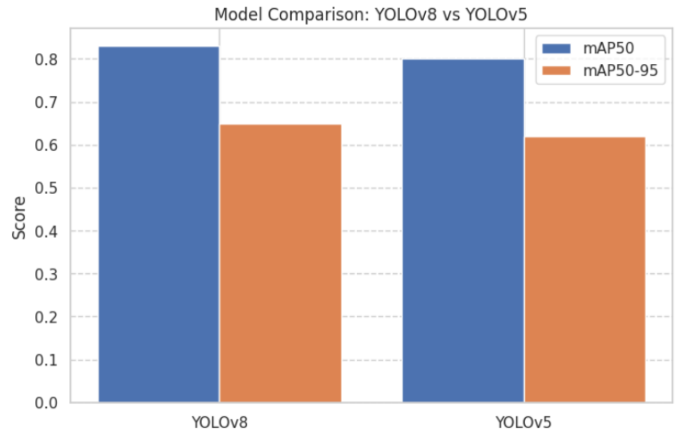
Accurate bounding box placements over the weed areas were shown by a visual comparison of predictions on test images, so supporting the model's robustness. Using the Google Colab interface, real-time inference was also tested with image uploads and on-demand weed detection; predictions were stored locally and on Google Drive for later review.

The YOLOv5 model was likewise trained using the same dataset and setup for benchmarking. The outcomes revealed somewhat lower YOLOv5 scores with:

- mAP@50: 0.80
- mAP@50-95: 0.62

Especially in terms of precision and generalization, this comparison underlined the better architecture and performance of YOLOv8.

Plotting of training dynamics including box loss, classification loss, and evaluation metrics across epochs also helped to track model convergence and stability. These graphs confirmed the quality of the dataset and the training strategy by showing consistent learning behavior free from any clear overfitting.



Ultimately, YOLOv8 has shown to be a better model than its predecessor YOLOv5 in key performance criteria and provides a consistent solution for real-time agricultural monitoring. It has also shown to be an efficient model for the job of weed detection using drone-based imagery.

VI CONCLUSION

This work effectively applied a YOLOv8-based model for weed detection and classification in agricultural fields utilizing a custom dataset. The model was trained and evaluated on annotated images; the results revealed high precision, recall, and mAP scores. The experimental results show that YOLOv8 offers accurate and efficient detection performance, so fitting for real-time weed identification tasks in precision agriculture. These measures support the model's resilience in identifying several kinds of weeds under several imaging environments. By allowing focused weed control measures, this method has the potential to drastically cut manual labor and improve crop management. Future research can be expanded by including it with drone or mobile robot platforms for automated weed surveillance in vast-scale farms. Furthermore improving accuracy is regular retraining using revised datasets. Researchers and agricultural experts can also use this work to compare YOLOv8 with other object detection models like YOLOv5 or Faster R-CNN, helping to select the most effective solution for specific field conditions.This study contributes to the development of smart agriculture tools, providing farmers with reliable AI-based solutions to monitor and manage weeds efficiently, ultimately boosting productivity and sustainability.

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