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Abstract.

Site-specific spraying guided by deep-learning detectors from the YOLO family can reduce herbicide use; however, under field conditions these models are prone to background false positives. Because soil is not represented as an explicit output class, bare-soil regions may receive confidence scores high enough to be detected as plants, triggering unnecessary herbicide applications. To address this limitation, we developed a Fuzzy Inference System (FIS) as a post-processing stage for a YOLOv9 detector used for weed recognition in soybean. The FIS reinterprets the detector's class confidence scores and estimates the probability of each plant class as well as an additional soil (background) class. The approach was evaluated using 624 UAV RGB image tiles acquired from a commercial soybean field over four dates between February and March 2024, comprising 5,860 manually annotated instances. The proposed FIS-YOLOv9 increased the overall mean Average Precision (mAP@50) by 1.42 percentage points compared with the baseline model and correctly reassigned 142 soil instances that had been incorrectly classified as plants. These results demonstrate that integrating a fuzzy post-processing layer into a modern object detector is an effective and computationally inexpensive strategy for reducing background false positives and the associated unnecessary herbicide applications in UAV-based precision weed management.

Keywords. *precision agriculture; weed detection; YOLOv9; fuzzy inference system; UAV imagery; site-specific spraying; deep learning.*

COMBINING YOLOV9 AND FUZZY INFERENCE SYSTEM TO IMPROVE THE PRECISION OF WEED RECOGNITION SYSTEMS IN SOYBEAN CROPS USING UAV IMAGERY

Introduction

Weeds are a major constraint on soybean productivity. Although uniform herbicide application remains the most practical control method, it increases production costs and environmental impacts by disregarding the actual spatial distribution of weeds. Site-specific weed management based on real-time detection has emerged as a promising strategy to overcome these limitations (Gerhards & Oebel, 2006). Recent advances in deep learning have enabled the development of accurate and computationally efficient object detectors, particularly those of the YOLO family, for deployment on UAVs and autonomous sprayers (Espejo-Garcia et al., 2020). Under field conditions, however, detection performance is affected by variations in illumination, soil texture, plant morphology, and crop growth stage. Among these challenges, false positives are particularly problematic in precision spraying because they trigger herbicide applications in areas where no weeds are present. Since YOLO handles background implicitly through objectness and confidence scores rather than as an explicit class, such errors are difficult to suppress using detection thresholds alone. Consequently, there is a need for post-processing approaches capable of explicitly discriminating background from vegetation. Fuzzy Inference Systems (FIS) are well suited to this task because they incorporate expert knowledge into flexible decision boundaries and can effectively handle uncertain inputs (Marwaha et al., 2025; Sujaritha et al., 2017). However, their application as a post-processing layer for modern deep-learning-based weed detectors remains largely unexplored. Therefore, this study developed and evaluated a FIS applied to the output of a YOLOv9 detector for weed identification in soybean. The proposed approach introduces an additional background class derived from the model's confidence values to reduce false positives and improve detection accuracy. The methodology was evaluated using UAV imagery acquired in commercial soybean fields at different crop development stages.

Materials and Methods

The proposed algorithm was validated on 624 RGB image tiles of a soybean field, captured over four dates between 7 February and 7 March 2024 at the Agronomic Experimental Station of UFRGS (EEA/UFRGS), Eldorado do Sul, RS, Brazil, spanning different crop vegetative stages and weed development periods. Images were acquired with a DJI Mini 3 Pro quadcopter at a target height of 4 m, chosen so the model could be deployed on a drone for real-time detection and because imagery above 10 m lacks the Ground Sampling Distance (GSD) needed to resolve small, early-stage weeds. Flight plans were generated with Litchi; owing to digital-elevation-model inaccuracies, the actual altitude ranged from about 4 to 10 m. The takeoff reference was set at the highest point of the terrain to avoid dangerously low flights, biasing deviations above 4 m, so the reported results reflect performance over this 4–10 m range.

Plants were manually annotated by bounding boxes using the open-source software LabelImg and assigned to one of three classes: soybean (the economic crop), Magnoliopsida (broad-leaf weeds), and Liliopsida (narrow-leaf weeds). The resulting dataset comprises 5,860 annotated instances. The dataset is markedly imbalanced toward the narrow-leaf class, which is later discussed as a limitation. A YOLOv9 model (Wang et al., 2024) was first trained in its original configuration as the baseline detector. Training and testing were implemented in Python with the TensorFlow library and executed on Google Colab, a hosted Jupyter Notebook environment that provides free access to GPU/TPU resources. A Fuzzy Inference System (FIS) (Marwaha et al., 2025; Sujaritha et al., 2017) was then appended to the YOLOv9 output to refine predictions and reduce false positives. The per-class confidence values from YOLOv9 feed the FIS, which outputs the occurrence probability of each plant class plus an additional soil (background) class. Because the detector does not represent background as a possible output, soil regions may be detected as plants; the explicit background class mitigates these false positives and the resulting unnecessary spraying of bare soil. The FIS was implemented in MATLAB R2020b. All experiments were validated using three-fold cross-validation. Detection performance was assessed by the mean Average Precision at an IoU threshold of 0.50 (mAP@50), comparing the baseline YOLOv9 against the proposed FIS-YOLOv9.

Results and Discussion

The annotated dataset comprised 5,860 instances distributed as 2,179 soybean, 2,781 broad-leaf, and 900 narrow-leaf objects (Table 1). The narrow-leaf class accounts for only about 15% of the instances, an imbalance revisited when interpreting the per-class results below. The YOLOv9 operating point was first defined under three-fold cross-validation by assessing the effect of the number of training epochs, learning rate, and input image size on mAP@50. Based on this optimization, all subsequent experiments used 200 epochs, a learning rate of 0.01, and an input size of 640×640 px; the full hyperparameter analysis is omitted here for brevity.

Table 1. Annotated instances forming the UAV image dataset (all acquired at EEA/UFRGS). Narrow = narrow-leaf weeds (Liliopsida); Broad = broad-leaf weeds (Magnoliopsida). Total instances: 5,860.

Week	Date	Tiles	Narrow	Broad	Soybean
S1	07 Feb 2024	349	153	192	1167
S2	23 Feb 2024	153	102	978	578
S3	01 Mar 2024	58	176	1013	205
S4	07 Mar 2024	64	469	598	229
Total		**624**	**900**	**2781**	**2179**

Effect of the fuzzy post-processing (FIS-YOLOv9)

The proposed FIS-based post-processing improved the overall detection performance of YOLOv9, increasing the mAP@50 by 1.42 percentage points. The improvement was most evident for the soybean class and for the overall performance metric, indicating that the additional background class helped reduce classification errors without compromising plant detection. At a confidence threshold of 0.05, FIS-YOLOv9 correctly assigned 142 soil instances to the background class, whereas the baseline YOLOv9 model, which lacks an explicit background output, assigned none and distributed these detections among the plant classes. By reconstructing a background class from the detector confidence values, the proposed FIS effectively reduced false positives associated with bare-soil regions, thereby decreasing detections that could otherwise result in unnecessary herbicide applications. These results indicate that appending a fuzzy post-processing stage to YOLOv9 is an effective, low-cost way to mitigate background-related false positives in UAV-based weed detection. The gain is modest in absolute terms but operationally relevant, since each avoided false positive corresponds to herbicide that would otherwise reach bare soil. The main limitation is the dataset’s class imbalance: the under-represented narrow-leaf class shows the weakest, most variable performance.

Conclusion or Summary

A Fuzzy Inference System applied as a post-processing layer to a YOLOv9 detector improved weed recognition in UAV imagery of soybean, increasing the overall mAP@50 by 1.42 percentage points and recovering an explicit soil (background) class that the baseline could not represent, thereby reassigning 142 soil instances that would otherwise trigger unnecessary spraying. The approach is simple, low-cost, and requires no retraining of the detector. Its main limitation is the dataset’s class imbalance, which penalizes the under-represented narrow-leaf class. Future work should enlarge and balance the dataset and field-test the integrated model on a UAV platform to confirm its potential to reduce herbicide use.

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