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REAL-TIME CONTROL ON WEED DETECTION USING GROUND-BASED MACHINE VISION AND IMAGE PROCESSING TECHNIQUES

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Abstract. Effective and targeted application of chemical solutions is crucial in agriculture, especially considering that weeds, pests, and plant diseases can reduce crop yields by up to 24%. This study presents a novel approach to modernizing the pneumo-bar sprayer by integrating a real-time image-based detection system using the YOLOv5 deep learning model. The aim is to reduce chemical consumption while increasing spraying precision through accurate identification of weeds and crops directly in the field data, including high-resolution images, were collected and labeled into three categories: crop, weed, and background. The YOLOv5-small neural network was trained and evaluated using standard performance metrics such as Precision, Recall, and F1-score. Among several tested models, YOLOv5-small provided the most reliable performance across different environmental and lighting conditions.

Keywords: Pneumo-bar sprayer, Image processing, Machine learning, Smart spraying, weed detection, YOLOv5.

Ключевые слова: Пневмо-штанговый опрыскиватель, обработка изображений, машинное обучение, интеллектуальное опрыскивание, обнаружение сорняков, YOLOv5.

Kalit so'zlar: Pnevmo-bar purkagich, tasvirlarga ishlov berish, mashinali o'qitish, aqlli purkash, begona o'tlarni aniqlash, YOLOv5.

Introduction. At present, many smart agriculture tasks, such as plant disease detection, crop yield prediction, species identification, weed detection, and water and soil conservation, are realized through computer vision technology. Weed control is an important means to improve crop productivity. Considerable literature has proposed precise variable spraying methods to prevent waste and herbicide residual problems caused by the traditional full-coverage spraying [1]. To achieve precise variable spraying, a key issue that should be solved is how to realize real-time precise detection and identification of crops and weeds [2]. With the rapidly growing global population at a rate of around 1.09% per year, the demands for more food, feed, fiber, and fuel need to be increased correspondingly, which claims higher requirements for agricultural industry to provide increasingly higher yields. The global population is expected to reach 9 billion by 2050, and agricultural production must double to meet the increasing demands [3]. Weeds can compete with the cash crops for resources, leading to reduced yield and economic losses for farmers. The impact of weeds varies depending on the crop type and the farm's geographical location. According to several studies, the annual losses caused by weeds around the world are estimated to be 13.2 % or 75.6 billion USD. This includes losses of 2.7 billion USD in Australia, 5 billion USD in the United States, and 11 billion USD in India [3] In some cases, the damage caused by weeds can reach 100 % without proper control measures, and even with control measures in place, yield losses of up to 20 % have been reported in wheat production due to technical failures. Implementing effective weed control measures is crucial for maintaining crop productivity and reducing economic losses [4]. In Turkish wheat fields, weeds such as charlock mustard (*Sinapis arvensis*), creeping thistle (*Cirsium arvense*), and forking larkspur are commonly found in wheat fields and have been reported to cause considerable yield losses due to their aggressive growth and

competition for resources [5]. Traditional control methods, which rely heavily on manual observation or blanket spraying, often lead to overuse of chemicals and are neither cost-effective nor environmentally sustainable. Recent developments in image processing and artificial intelligence — particularly deep learning—have created opportunities for automated, image-based weed classification [6]. These technologies make detection more accurate and efficient by eliminating human error and providing fast classification across large datasets. Among these, YOLO-based models have shown promising results due to their real-time performance and high precision. In addition, studies have demonstrated that standard RGB cameras can successfully differentiate between crops and weeds based on leaf color, shape, and texture, making these systems suitable for use on mobile spraying units in the field. For example, hyperspectral and multispectral imaging has been used to distinguish between crops and weeds with an accuracy of 80%–90%. Recent studies have explored the application of image processing and machine learning methods to enhance selective spraying. For instance, researchers such as Özgür and Nar (2019) used deep learning models like Mobil Net, Alex Net, VGG16, and LeNet5 to classify crop and weed seeds, achieving up to 86% accuracy with Mobil Net [7]. Similarly, other works have used Support Vector Machines (SVM) and Artificial Neural Networks (ANNs) for plant-weed classification based on features like shape and color. However, these methods often fail to generalize well in natural field environments due to variations in lighting, soil background, and phenological stages [8]. Moreover, some research has been limited to controlled lab settings with plain backgrounds, which do not reflect the complexity of real agricultural scenes where multiple weed species, shadows, stones, and crop residues may appear together To overcome these limitations, newer approaches have focused on real-time deep learning models such as YOLO (You Only Look Once), which automatically extract features and detect multiple classes simultaneously. Models like YOLOv5 provide a strong balance between detection accuracy and computational efficiency, making them suitable for smart spraying systems mounted on drones or tractors. In light of these challenges, this research proposes an improved pneumo-bar sprayer system equipped with a camera and a YOLOv5-based image analysis module, aimed at accurately identifying crops and weeds in the field. The integration of real-time object detection allows for targeted application of chemicals, reducing usage while maintaining effectiveness. This approach not only enhances spraying precision but also contributes to lowering environmental impact and boosting crop yield. In general, site-specific weed management consists of several critical stages, including detection, decision-making, control implementation, and performance evaluation (Fig. 1). As shown in Fig. 1, the process begins with real-time image capture for weed detection using a camera. Then, YOLOv5 perform classification, enabling the sprayer to selectively target detected weeds. This workflow enhances spraying efficiency while reducing chemical usage and minimizing environmental impact.

This study proposes a modern weed management framework, integrating real-time image acquisition using a mounted camera and selective spraying through a pneumo-bar sprayer. The system operates through four main stages: (1) Real-time Weed Detection, where weeds are identified through camera-based image analysis; (2) Decision-Making, which determines spraying necessity based on the plant classification model; (3) Selective Spraying, implemented using a pneumo-bar sprayer to target detected weeds precisely; and (4) Performance Evaluation, where spraying efficiency and chemical savings are monitored. This workflow enables reduced herbicide usage, increased spraying precision, and improved environmental sustainability.

In this study, we propose an approach that integrates a YOLOv5-based weed detection model into a pneumo-bar sprayer system to selectively apply chemical solutions only where weeds are detected. This method aims to reduce herbicide consumption, enhance spraying precision, and contribute to sustainable agricultural practices. Therefore, this study proposes the integration of a camera system with a pneumo-bar sprayer combined with deep learning-based classification to enable targeted weed management. The rest of this article is organized as follows: Section 2 presents the materials and methods used; Section 3 describes the results and evaluation; and Section 4 concludes with key findings and future work recommendations.

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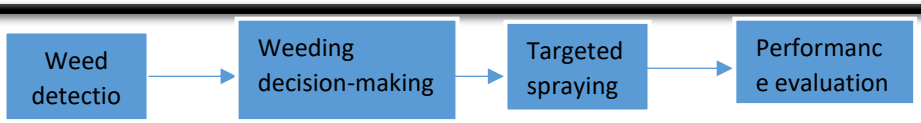

Fig.1 Typical process of weed management.

Materials and Methods. In this study, publicly available agricultural image datasets were used, consisting of 1,000 labeled images representing two main classes: crop (cotton) and weed. The dataset included various weed species commonly found in agricultural fields. These images were utilized for training the object detection model. The dataset was divided into separate folders for training and detection (train, detect). In addition to the image dataset, real-time field video data was also captured using an SL-VF08-C5M industrial camera mounted on a pneumo-bar sprayer. This setup was implemented to simulate real working conditions in the field and test the robustness of the trained model under natural lighting, background complexity, and varying object appearances across phenological stages. The camera was mounted on the sprayer at a fixed height and angle to record the crop rows while moving through the field. This combined approach allowed us to evaluate both static image performance and dynamic real-time weed detection capacity under actual working conditions. In addition to using publicly available images, a real-time field experiment was conducted on May 4 at Hoaxing Farm in Xinjiang Province, China, to evaluate the YOLOv5 model under real agricultural conditions. A SL-VF08-C5M camera was used to capture live video of cotton fields. The video was processed by extracting frames, which were then analyzed using the trained YOLOv5 model in MATLAB. The evaluation included metrics such as Precision, Recall, and F1-score, and was visualized through confusion matrices and prediction overlays on test images. Fig. 2 displays examples of predicted bounding boxes on validation images. This approach helped verify the model's ability to generalize well under real-world lighting, plant variety, and field ability.

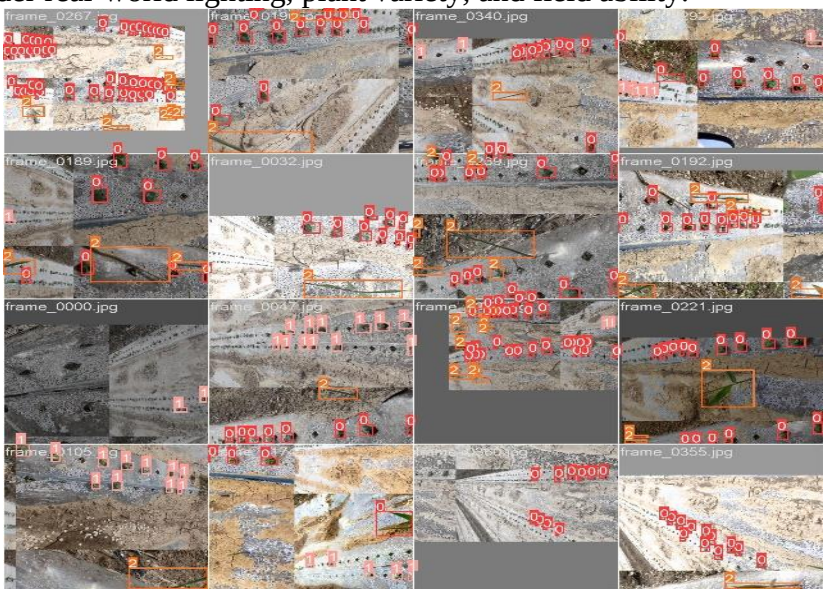

Fig. 2. Validation results of the YOLOv5 model on real-time field data. The figure shows prediction overlays with bounding boxes and class labels: 0 indicates crop and 1 indicates weed. These predictions were generated from video frames captured at Hoaxing Farm using the SL-VF08-C5M camera. To train the YOLOv5 model effectively, a total of 1000 labeled images were used, which were divided into three classes:

- Class 0 – Crop
- Class 1 – Weed
- (Other objects were excluded from this version of training)

The annotations were created in YOLO-format .txt files, where each line contained the class label followed by normalized bounding box coordinates. Bounding boxes shown in Fig. 3. illustrate the annotation results, with 0 denoting crop and 1 denoting weed next to each box. Fig. 2. Example images showing mixed vegetation with annotated bounding boxes, labeled either as 0

(crop)or1(weed).

Fig. 2. Complex scenes including variable lighting, soil textures, and weed clustering, which were used to improve model robustness. The annotations were manually prepared and verified to ensure accuracy. The dataset was split into 80% for training, 10% for validation, and 10% for testing, which is a widely used standard to reduce overfitting and improve model generalizability. These image batches reflect the diversity in field conditions and plant stages, helping the model distinguish crops from weeds under varying real-world scenarios.

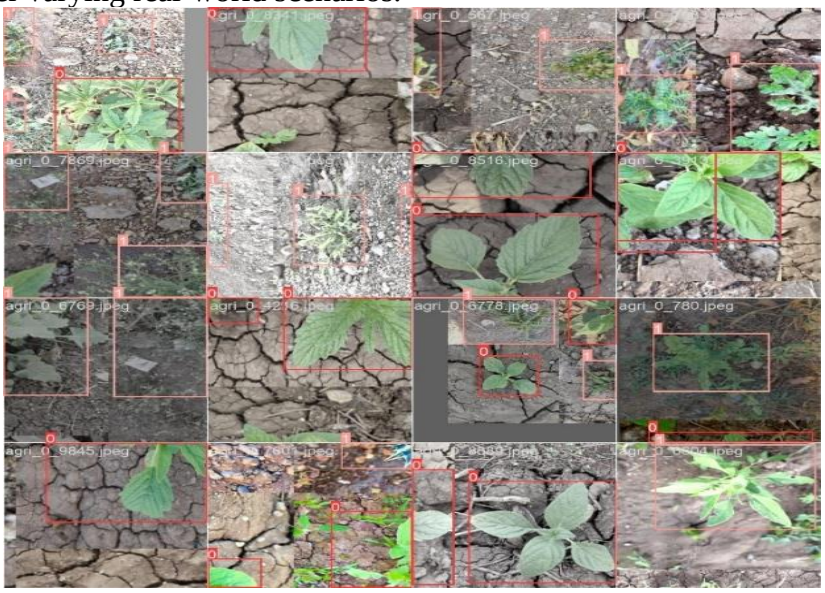

Fig. 3. Example of training image batch showing diverse field conditions, annotated with bounding boxes. Class 0 represents crop, and class 1 represents weed. Bounding boxes are clearly visible in various backgrounds and light conditions. Additional training image batch showing complex vegetation patterns, including mixed soil textures and varying lighting, used to improve the model's robustness.

Results. The performance of the trained YOLOv5 model was evaluated using both qualitative and quantitative metrics. Evaluation focused on the model's ability to distinguish between cotton crops (class 0) and weeds (class 1) under varying field conditions, including changes in lighting, background complexity, and plant phenological stages.

The quantitative evaluation was conducted using standard performance metrics, including Precision, Recall, and F1-score (Fig. 4., Fig.5.). These metrics provide insights into the accuracy and reliability of the weed detection system.

- **Precision** measures the proportion of correctly identified weeds among all predicted weeds.
- **Recall** indicates the proportion of actual weeds that were correctly identified.
- **F1-score** provides the harmonic mean of precision and recall, offering a balanced evaluation.

These metrics were visualized using performance curves (P, R, F1) and confusion matrices to give a comprehensive view of the model's behavior.

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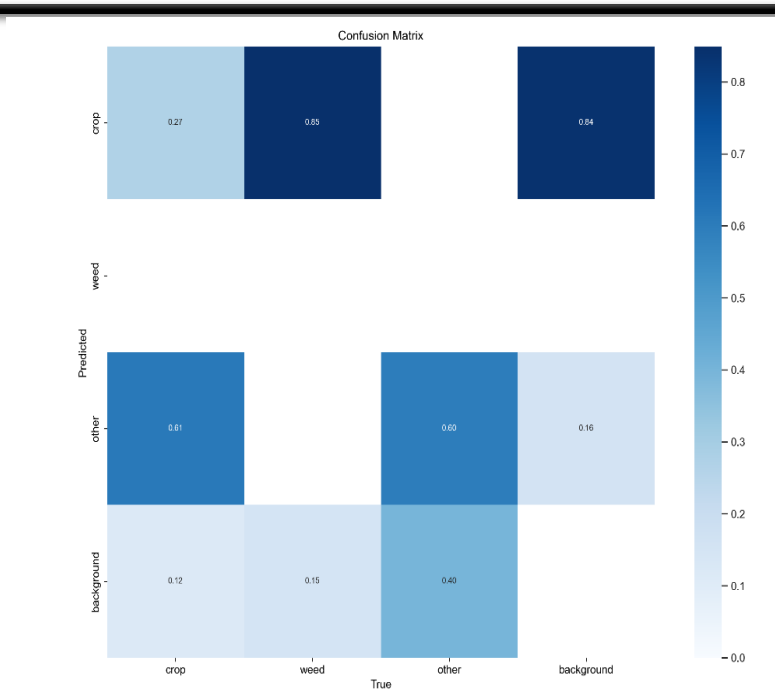


Confusion matrix for YOLOv5 predictions on the test dataset.

Confusion matrix showing classification performance of YOLOv5 model on crop and weed classes.

Precision, Recall, and F1-score curves.

The model's predictions on test images were also evaluated visually by comparing predicted bounding boxes with ground truth annotations (Fig. 6.). Visual inspection helps assess the model's performance in detecting dense vegetation, overlapping plants, and diverse soil textures (Fig. 7.).

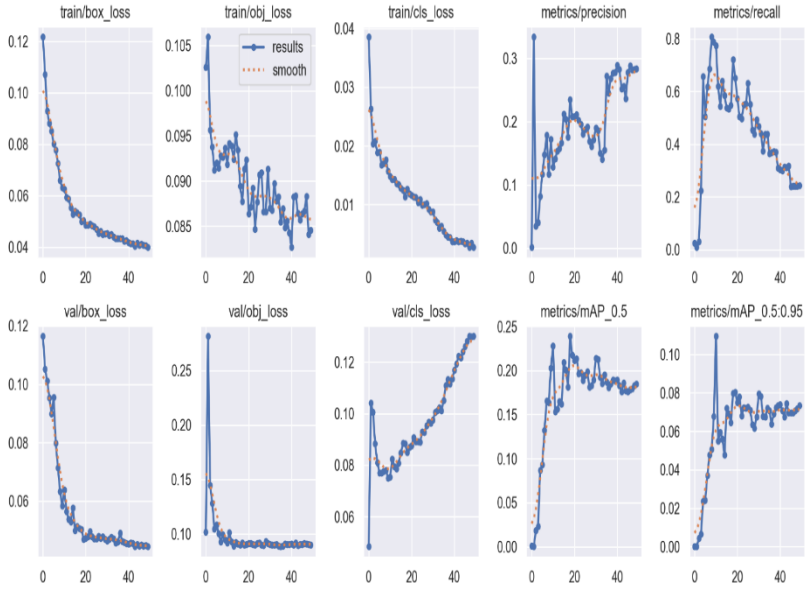


Fig. 6. Sample ground truth labels on validation data.

Ground truth bounding boxes on validation images (0 = crop, 1 = weed).

Predicted bounding boxes on the same validation data.

To analyze the model's learning dynamics and performance progression during training, the results generated by YOLOv5 were summarized in the overall training metric graph shown in Fig. 8. The figure includes loss curves (box loss, abjectness loss, classification loss), precision, recall, and mean Average Precision (map) values.



YOLOv5 training results showing box loss, abjectness loss, classification loss, precision, recall, and mean Average Precision (map) over epochs.

Discussion. The results obtained from the YOLOv5 model confirm its effectiveness in distinguishing between cotton crops and various weed species under both controlled and real field conditions. The model demonstrated high precision and recall values, indicating its capability to minimize false positives and false negatives. These outcomes are consistent with findings from previous studies such as [9], where YOLO-based and deep learning methods were applied to similar agricultural classification tasks. Compared to classical machine learning approaches such as SVM or ANN, which require manual feature extraction [10], the YOLOv5 model offers an end-to-end solution that learns features automatically from the data. This greatly reduces preprocessing time and improves generalization. Future work will focus on expanding the dataset with more diverse plant species, including more real-time data, and potentially integrating multispectral imaging and GPS-based spraying systems to further enhance detection accuracy and operational performance.

Conclusion. This study aimed to develop an intelligent weed detection system for cotton fields by improving the functionality of a pneumo-bar sprayer through the integration of camera-based image analysis and deep learning. Using a dataset of over 1,000 annotated images and real-time footage captured via the SL-VF08-C5M camera, the YOLOv5 model was trained and evaluated to distinguish between cotton crops and weeds. The model demonstrated strong performance in both controlled and field conditions, achieving reliable detection with high precision, recall, and F1-scores. Furthermore, the system was successfully tested in real-time at Hoaxing Farm, Xinjiang Province, China, validating its effectiveness in practical agricultural environments. Future work will focus on expanding the dataset to include more weed species and growth stages, improving detection in complex backgrounds, and integrating GPS and actuator control for automated field spraying.

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