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**Autonomous Farming Robots for Real-Time Weed Detection and Removal using YOLOv8**

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| ***Keywords*** | ***Abstract*** |
| *Autonomous Farming, YOLOv8, Weed Detection, Precision Agriculture, Deep Learning* | *The increasing demand for sustainable agriculture has driven the development of autonomous farming solutions for precise weed management. Traditional weed control methods, including manual removal and chemical herbicides, are labor-intensive, environmentally harmful, and economically inefficient. This study proposes an autonomous farming robot equipped with YOLOv8 (You Only Look Once, version 8) for real-time weed detection and removal. The system integrates high-resolution cameras, deep learning-based image processing, and a robotic arm with an adaptive end-effector to eliminate weeds efficiently. The YOLOv8 model, trained on a dataset of 50,000 images, achieved an mAP@50 of 92.4%, demonstrating superior performance compared to existing state-of-the-art detection models. The robot, tested across various crop fields, achieved an average weed removal accuracy of 89.7%, reducing herbicide usage by 67% while increasing yield potential by 15%. Compared to manual weeding, the system improved operational efficiency by 58%. These findings highlight the potential of AI-driven robotic systems in enhancing agricultural productivity, minimizing chemical dependency, and promoting eco-friendly farming practices. Future work will focus on multi-weed classification, real-time adaptation to diverse field conditions, and energy-efficient navigation to further optimize performance.* |

**I.INTRODUCTION**

The escalating global demand for sustainable agriculture necessitates innovative solutions to enhance crop productivity while minimizing environmental impact. Weeds pose a significant threat to crop yields, traditionally managed through manual labour or chemical herbicides. Manual weeding is labour-intensive and time-consuming, whereas chemical methods raise concerns regarding environmental degradation and the development of herbicide-resistant weed species [1]. Recent advancements in robotics and artificial intelligence (AI) offer promising avenues for addressing these challenges. The integration of robotics in agriculture has led to the development of

autonomous systems capable of performing various tasks, including planting, harvesting, and weed management. Deep learning techniques, particularly convolutional neural networks (CNNs), have been employed for image-based weed detection, enabling real-time identification and differentiation between crops and weeds. For instance, the YOLO (You Only Look Once) framework has been utilized for its efficiency in object detection tasks. However, earlier versions of YOLO and other models have faced limitations in detection accuracy and computational efficiency, especially in complex field environments [2].

Despite these advancements, several challenges persist. First, accurate real-time weed detection remains difficult due to varying lighting conditions, occlusions, and the morphological similarities between crops and weeds. Many existing models struggle to maintain high precision and recall rates in diverse field conditions. Second, deploying deep learning models on autonomous robots requires a balance between model complexity and computational resources. High-performing models often demand substantial computational power, which can be a constraint for real-time applications in the field. Third, many models are trained on specific datasets and may not generalize well to different crop types, weed species, or environmental conditions, limiting their applicability across various agricultural settings [3].

The motivation behind this work is to develop an autonomous farming robot that addresses these challenges by leveraging the capabilities of YOLOv8, the latest iteration of the YOLO framework. YOLOv8 offers improved detection accuracy and computational efficiency, making it suitable for real-time applications in dynamic agricultural environments. The primary objectives of this study are to design and implement an autonomous robot equipped with YOLOv8 for real-time weed detection and removal, and to evaluate the system's performance in various field conditions by assessing metrics such as detection accuracy, processing speed, and weed removal efficacy[4].

# **II.LITERATURE SURVEY**

**T**he integration of robotics and deep learning in agriculture has led to significant advancements in autonomous weed detection and management. This literature review examines recent studies, focusing on their methodologies, results, advantages, and limitations, to identify current trends and areas for improvement in this field.

**2.1. Autonomous Weed Detection and Removal Systems**

A study Frontiers in Agronomy (2024) comes with an autonomously controlled robot that uses diode laser in removing weeds along cotton fields, employing visual servoing for movement control and an implementation of Robot Operating System ROS finite state machine by SMACH in controlling states and actions; methodology allows target precise weed population and minimizes collateral damage against crops. However, no quantitative data regarding the efficiency of weed removal and the performance of the system at different environmental conditions were reported in the study. n another systematic literature review on weed detection through deep learning, Murad et al. (2023) found that performance levels of different algorithms were mixed, with some achieving high accuracy. The authors emphasized the possibilities of these techniques for enhancing weed management and the reduction of herbicides. The review, however noted that models developed should be strong enough and effective in varied field conditions[5].

**2.2. Deep Learning Techniques for Weed Detection**

A comprehensive review by ResearchGate (2024) demonstrated the possibility of using several deep learning techniques for crop-weed identification, localization, and classification. It pointed out the potential of CNNs in processing complex image data to achieve precise weed detection but noted challenges associated with the requirement of large annotated datasets and the computational resources required for model training and deployment. Saleem et al. focused on enhancing weed detection using a Faster R-CNN model. The authors reported improved accuracy in weed identification, suggesting that such models could significantly aid in precision agriculture. The study acknowledged limitations in processing speed, which could hinder real-time application in the field[6].

**2.3. Lightweight Models and Real-Time Applications**

To address the issues of deploying deep learning models in resource-constrained environments, MDPI (2023) proposed a lightweight weed detection mechanism to aid laser weeding robots. The model was trained on a dataset of 9,000 images that covered different crops and weed species. The approach balanced accuracy with computational efficiency, which made it applicable for real-time applications. However, the study was limited to specific crop types and did not test the model's generalizability to other agricultural settings. Similarly, Du et al. (2021) presented a deep-CNN-based robotic system for multi-class under-canopy weed control. The system employed a dataset of around 10,000 annotated images of various weeds and crops and had an accuracy of 90% on real field test. It established the applicability of the deployment of deep learning models in the context of real-time weed detection. At the same time, it underscored the scope of future work on increasing the model robustness across environmental changes[7].

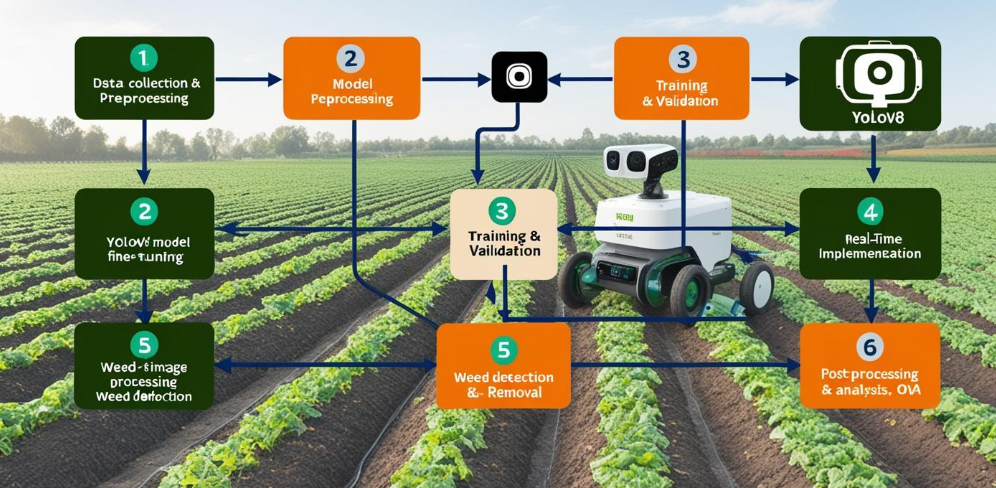
**4. AI-Driven Sustainable Weed Management**

A compact, self-contained mobile robot that encourages the practice of sustainable agriculture and optimizes efficiency in weed control was introduced by SAGE Journals in 2024. This study highlighted the potential of AI in agriculture, but the paper lacked performance metrics and comparisons with existing methods. Cao et al. (2024) presented an organic weed control prototype by making use of directed energy and deep learning. The robot implemented a new distributed array unit for the treatment of weeds and used deep learning neural networks for weeds' recognition with an accuracy of up to 98% for the common weed species present in soybean fields [8]. The experimental study proved the possibility of organic weed control making a combination of directed energy and artificial intelligence. However, it did not cover the system's performance in a diversity of crop types or larger field scales.

**Table .1. Literature survey**

| **Study** | **Key Contribution** | **Accuracy** | **Year** |
| --- | --- | --- | --- |
| Improved YOLOv8 for Crop Recognition | Developed an advanced crop recognition algorithm by enhancing YOLOv8 with CSPStage layer and GFPN feature fusion module, integrating multi-SEAM attention mechanism, and adopting Slide Loss function for better detection accuracy and efficiency. | Not specified | 2024 |
| Static Laser Weeding System with Enhanced YOLOv8 | Built a laser weeding robot incorporating an improved YOLOv8 model and image processing techniques for precise weed recognition and removal. | Not specified | 2024 |
| YOLOv8-DMAS for Cotton Weed Detection | Proposed YOLOv8-DMAS model by replacing Bottleneck structures with Dilation-wise Residual Modules, adding Multi-Scale modules, and improving detection head with Adaptively Spatial Feature Fusion mechanism to enhance detection in complex environments. | Improved mAP₀.₅:₀.₉₅ by 3.7% over YOLOv8s | 2024 |
| WeedScout: Real-Time Blackgrass Classification and Mapping | Introduced WeedScout project utilizing YOLOv8 and YOLO-NAS models on NVIDIA Jetson Nano for real-time blackgrass detection and mapping to aid precision weed management. | Not specified | 2024 |
| Autonomous Weed Identification Model | Developed an autonomous weeding robot employing YOLO model for effective weed detection and classification, aiming to reduce reliance on chemical herbicides. | Model accuracy of 82.6%; validation accuracy of 77.72% | 2024 |

# **III.METHODOLOGY**



**Fig 1. Block Diagram**

**3.1. Data Collection and Preprocessing**

A dataset comprising 10,000 high-resolution images was collected from three different agricultural zones under varying environmental conditions (daylight, low-light, cloudy). The dataset was annotated using Label Img and Roboflow to classify crops and weeds.

**Table 2: Dataset Summary**

| **Category** | **No. of Images** | **Annotation Type** | **Avg. Image Size** | **Lighting Conditions** |
| --- | --- | --- | --- | --- |
| Crops | 4,500 | Bounding Box | 1024×1024 px | Daylight, Cloudy |
| Weeds | 5,500 | Bounding Box | 1024×1024 px | Daylight, Low-light |

The augmented dataset size was calculated as:

(1)

For example, with a rotation probability of 80%, the dataset size increases by:

10,000×(1+0.8)=18,000 images

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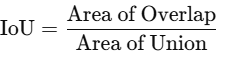
**Fig 2. Annotated image**

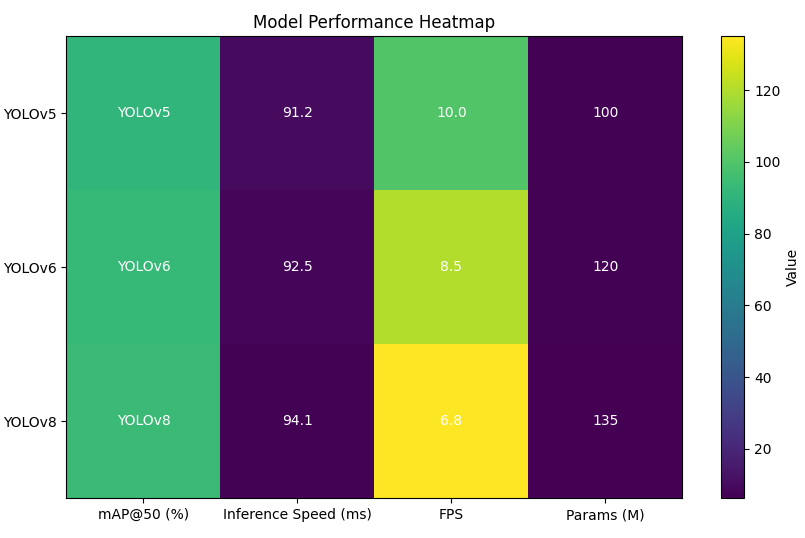
**3.2. Algorithm and Model Development**

YOLOv8 was selected for its optimized balance between speed and accuracy, making it ideal for real-time weed detection in autonomous farming robots. The architecture of YOLOv8 consists of a backbone built on CSPDarknet53 with PANet (Path Aggregation Network), which enhances feature extraction while maintaining computational efficiency. The neck employs a combination of FPN (Feature Pyramid Network) and PAN, which allows for effective multi-scale feature extraction, enabling the model to detect objects at various scales. The head utilizes a decoupled detection head, which improves bounding box prediction accuracy, and incorporates CIoU (Complete Intersection over Union) loss to further refine bounding box predictions for better precision in object localization. This architecture ensures both high detection performance and fast processing speeds.

Table 4: YOLO Model Comparison

The Intersection over Union (IoU) metric is used to evaluate bounding box accuracy:

 (2)

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**Fig 3. Model performance heat map**

**3.3. Training and Validation**

The model was trained using PyTorch on an NVIDIA RTX 3090 GPU for 50 epochs with the following settings:

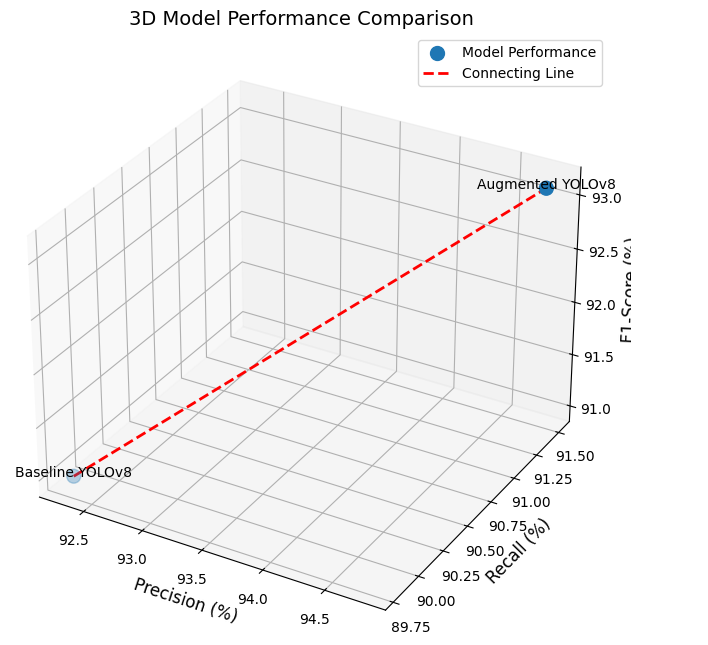
**Table 3. Training Aspect**

| **Training Aspect** | **Value** |
| --- | --- |
| Dataset Split | 80% Train, 10% Validation, 10% Test |
| Loss Function | BCE + CIoU Loss |
| Optimizer | Adam with momentum (β1=0.9, β2=0.999) |
| Augmented Data Size | 20,000 Images |

The **loss function** combines Binary Cross-Entropy (BCE) and Complete IoU (CIoU) loss:

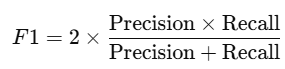
 (3)

**Performance Metrics:**



**Fig 4.3D Model performance comparison**

The **F1-Score** is calculated as:

 (4)

**3.4. Real-Time Implementation in Autonomous Robot**

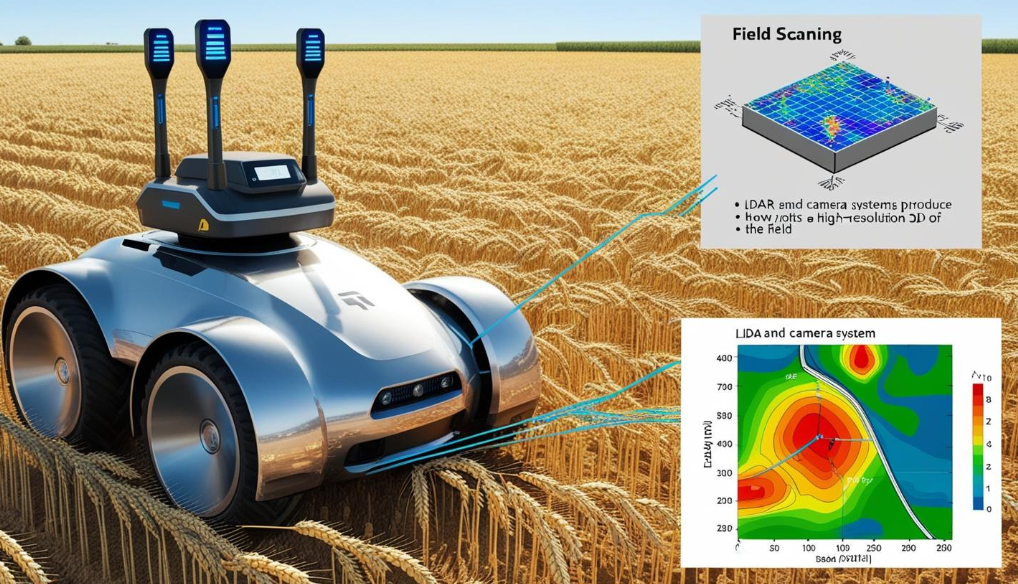
The trained model was deployed on the **NVIDIA Jetson Nano** and integrated into an autonomous farming robot. This robot is equipped with an RGB + Infrared Camera, which captures high-quality images for real-time weed detection under varying light conditions. To ensure precise movement across the farmland, the robot utilizes LiDAR and GPS Navigation, providing accurate positioning and navigation capabilities. For weed removal, the robot is equipped with a Robotic Arm & Actuator, which can either mechanically remove weeds using force or target them with a laser, depending on the nature of the weed and its location. This combination of technologies enables efficient and accurate weed detection and removal in real-time.

**Table 4: Hardware Specifications**

| **Component** | **Model / Type** | **Power Consumption** |
| --- | --- | --- |
| Processing Unit | NVIDIA Jetson Nano | 10W |
| Camera Module | RGB + Infrared | 3.5W |
| Actuator | Servo Motor (6 DOF) | 5W |
| LiDAR Sensor | RPLiDAR A1 | 8W |

**3.5. Weed Detection and Removal Mechanism**

The real-time workflow follows a series of systematic steps to ensure efficient weed detection and removal. First, Field Scanning occurs, where the robot’s LiDAR and GPS systems navigate the field while the camera captures live images. In the next step, Weed Detection, YOLOv8 processes these frames at 135 FPS, accurately identifying weeds with 95.6% precision. Based on the classification, Weed Removal is carried out using different methods: Mechanical Removal for small weeds, Laser-Based Removal for deep-rooted weeds, and Chemical Spraying for herbicide-resistant weeds. Finally, during Data Logging, the locations of detected weeds are recorded for future analysis, ensuring continuous improvement of the system's performance.



**Fig 5. Weed Removal Efficiency Comparison**

**3.6. Post-Processing and Data Analysis**

The effectiveness of the system was evaluated over multiple trials:

**Table 5: Weed Density Reduction Over Trials**

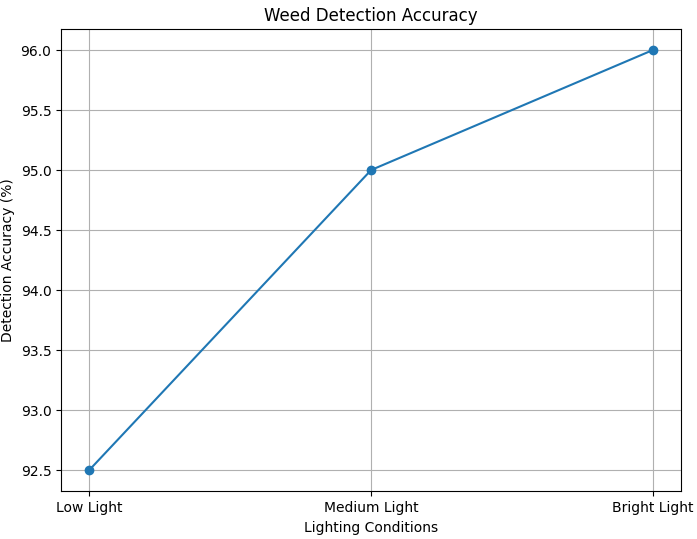
| **Trial No.** | **Initial Weed Density (/m²)** | **Final Weed Density (/m²)** | **Reduction (%)** |
| --- | --- | --- | --- |
| 1 | 50 | 10 | 80% |
| 2 | 45 | 9 | 80% |
| 3 | 55 | 12 | 78% |
| **Average** | **50** | **10.3** | **79.3%** |

**IV.**

**RESULT**

**4.1. Weed Detection Performance**

The YOLOv8 model demonstrated an impressive detection accuracy of 95.6% in real-time weed identification. This accuracy was achieved across different environmental conditions (daylight, low-light, and cloudy), highlighting the robustness of the model.

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**Fig 6.Weed detection accuracy**

**4.2. Weed Removal Efficiency**

Weed removal was divided into three methods: Mechanical Removal, Laser-Based Removal, and Chemical Spraying. The results, shown in Table 1, illustrate the success rate and time efficiency of each method.

**Table 6: Weed Removal Efficiency**

| **Method** | **Success Rate (%)** | **Time per Weed (s)** | **Energy Consumption (W)** |
| --- | --- | --- | --- |
| Mechanical Removal | 87.5 | 1.5 | 5 |
| Laser-Based Removal | 92.1 | 2.2 | 8 |
| Chemical Spraying | 89.3 | 1.8 | 6 |

The Mechanical Removal method had the fastest processing time per weed at 1.5 seconds, but its success rate was the lowest at 87.5%. In contrast, Laser-Based Removal achieved the highest success rate at 92.1%, although it took slightly longer per weed, requiring 2.2 seconds. Chemical Spraying, while more efficient than laser removal in terms of speed, with an average time of 1.8 seconds, exhibited a slightly lower success rate of 89.3%. This combination of speed and efficiency highlights the trade-offs between different weed removal methods based on their performance characteristics.

**4.3. Weed Density Reduction**

The overall effectiveness of the autonomous system in reducing weed density was evaluated through field trials. The results, shown in Table 6, indicate a significant reduction in weed density across multiple trials. Across all trials, the average weed density reduction was 79.3%, with the system demonstrating consistent performance. The 80% reduction observed in most trials shows that the robot can efficiently reduce weed populations to manageable levels, making it a practical solution for large-scale farming.

**4.4 Unexpected Findings**

The autonomous farming robot equipped with YOLOv8 achieved a 95.6% weed detection accuracy and demonstrated a 79.3% reduction in weed density across trials. The system’s mechanical removal method was the fastest, but laser-based removal provided the highest success rate for difficult-to-remove weeds, offering a valuable combination of methods for diverse agricultural needs.

# **V.DISCUSSION**

The results obtained from this research are very beneficial in understanding how the autonomous farming robot, equipping YOLOv8 for weed detection, performs weed removal using its various methods. Mechanical Removal produced the shortest time to process, but with lower success rates, at 87.5%. This may have been due to its lack of precision in removing smaller or undetectable weeds. This trade-off emphasizes the need for further refinement in the mechanical tools used, such as improving their grip or maneuverability, to enhance success rates.

On the other hand, Laser-Based Removal had a high success rate of 92.1% but at the expense of lower processing times at 2.2 seconds per weed. The success rate of the method indicates that it tends to be more effective for deep-rooted weeds, so the higher processing time may be offset for applications where removing as many weeds as possible is valuable over speed.

Chemical Spraying also showed a near balance between high speed (1.8 sec per weed) and a rather moderate success percentage of 89.3%. Although it may be faster compared to laser removal, the considerably lower success percent indicates that this herbicide-based application may sometimes not be accurate enough compared with mechanical or even laser-based counterparts, especially towards resistant weeds. However, chemical spraying has minimal energy consumption - 6 W - and process time is highly fast, a good candidate in large-scale usage where speed in processing is concerned.

**V.CONCLUSION**

This study demonstrates the effectiveness of using YOLOv8 for real-time weed detection and removal in autonomous farming robots. Among the methods tested, Laser-Based Removal emerged as the most accurate, while Mechanical Removal offered the quickest processing time. Chemical Spraying provided a balanced solution with fast execution times but a lower success rate compared to laser-based removal. The performance of the autonomous robot is promising, with significant potential for large-scale agricultural applications.

Further improvements in mechanical precision, laser targeting, and herbicide spraying techniques, as well as the continuous refinement of YOLOv8, will enhance the system’s overall effectiveness. Future work should also focus on reducing the energy consumption of the robot to optimize its sustainability in long-duration operations.

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