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Research Article

Smart Agriculture in the Fight against Weeds: Analyzing the Impact of Image Quality on Deep Learning Performance

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Abstract:

Weed management is a critical challenge for sustainable agriculture, driving the adoption of Smart Farming solutions that integrate the Internet of Things (IoT) and deep learning. While significant research focuses on improving object detection algorithms, the influence of data quality from IoT perception devices on system performance remains underexplored. This paper presents a holistic study of an IoT-aligned weed detection framework, using the YOLOv8 model to investigate the impact of image data quality versus quantity. We train and evaluate two identical YOLOv8n models on contrasting datasets: a high-quality, smaller dataset (D1, n=512) and a larger, lower-quality dataset (D2, n=5,061). Our results show a decisive advantage for data quality: the model trained on D1 achieved a mean Average Precision (mAP@50) of 0.90, significantly outperforming the model trained on D2 (mAP@50 of 0.82), alongside higher precision (0.88 vs. 0.74). This empirical evidence underscores that for robust IoT-based detection systems, investing in high-fidelity data acquisition at the Perception Layer is more effective than merely amassing larger volumes of data. The findings offer a practical design principle for developing reliable and efficient smart agriculture solutions, emphasizing the need for system-level optimization beyond algorithmic choice.

1. Introduction

Weeds remain one of the most significant biotic constraints to global agricultural productivity, competing directly with crops for essential resources [1]. Conventional management, reliant on the broadcast application of herbicides, is increasingly unsustainable, leading to environmental pollution, herbicide resistance, and unnecessary economic costs [2, 3]. There is a pressing need for precision in weed control-a core tenet of sustainable agriculture.The advent of Smart Agriculture, powered by the synergy of the Internet of Things and Artificial Intelligence, offers a transformative pathway [4, 5]. IoT provides the architectural framework for the digitization of farms, deploying a network of sensors and devices that generate real-time, high-resolution data from the field [6, 7]. Concurrently, advances in computer vision and deep learning provide the analytical intelligence to interpret this visual data, automating tasks from monitoring to identification [8, 9].A complete smart weed detection system follows an integrated IoT pipeline: Perception (e.g., UAV-based image capture), Transmission, Intelligent Processing (e.g., cloud-based deep learning model), and Application [10, 11]. This closed-loop system promises to convert raw field data into precise, actionable insights [12].However, the research focus has predominantly been on optimizing the Processing layer, comparing model architectures and reporting incremental gains in accuracy metrics [13, 14]. A critical, system-level factor has been relatively overlooked: the profound impact of the inherent quality of data generated by the Perception layer on the overall system's performance [15, 16]. In practice, the choice between collecting high-fidelity imagery or a larger volume of lower-quality data is a fundamental design decision whose consequences are not well quantified.

Contributions of This Work

This study addresses this gap by investigating the data quality-quantity trade-off within a realistic IoT-aligned framework. Our contributions are threefold:

- **System Framework:** We detail the implementation of a reproducible, end-to-end weed detection pipeline using the state-of-the-art YOLOv8 model within a standard IoT workflow.
- **Empirical Analysis:** We conduct a controlled experiment, training identical models on two distinct datasets: a high-quality, smaller dataset (D1) and a larger, lower-quality dataset (D2).
- **Design Insight:** We demonstrate conclusively that superior data quality yields significantly better detection performance (mAP@50: 0.90 vs. 0.82) than a larger volume of inferior data. This provides an evidence-based guideline for prioritizing Perception Layer standards in smart farming system design.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 provides necessary background. Section 4 describes our methodology. Section 5 presents and discusses the experimental results. Finally, Section 6 concludes the paper.

2. Related Work

The Internet of Things (IoT) has emerged as the foundational framework for modernizing agriculture, transitioning it from a labor-intensive practice to a data-driven science [6, 17]. An IoT system in agriculture is typically architected in layers: a Perception Layer comprising sensors and actuators; a Transport Layer for data transmission; a Processing Layer for cloud or edge analytics; and an Application Layer delivering actionable insights [5, 18]. This architecture enables the real-time monitoring of critical parameters such as soil moisture, micro-climate, and crop health, forming the basis for Precision Agriculture [7, 19]. By providing a closed loop from data acquisition to automated intervention, IoT frameworks have proven effective in optimizing resource use, particularly in irrigation and fertilization management [10, 20].Within this IoT ecosystem, weed management stands out as a high-impact application due to the significant economic and environmental costs associated with uncontrolled weed growth [1, 21]. The pursuit of precision weed control has directly driven innovation within the Perception Layer. The sensor paradigm has evolved from static soil probes to mobile imaging platforms, most notably Unmanned Aerial Vehicles (UAVs) [22, 23]. UAVs act as intelligent, mobile sensor nodes, capable of capturing high-resolution RGB and multispectral imagery over vast fields, providing the spatial coverage required for selective treatment [24, 25]. This shift from point-based to area-based sensing has created a paradigm where the primary data input for weed management is no longer scalar readings but high-volume visual data streams [26].The deluge of visual data from UAVs necessitated automated analysis, leading to the integration of Artificial Intelligence, and specifically deep learning, into the IoT Processing Layer. Early integrated systems deployed simpler Convolutional Neural Networks (CNNs) for image classification on edge devices like Raspberry Pi, demonstrating the feasibility of *IoT-enabled* weed identification [27]. However, for precision spraying or mechanical weeding, simple classification is insufficient; precise, real-time localization of weeds is required. This operational need catalyzed the adoption of state-of-the-art object detection models within the IoT pipeline. Models from the *You Only Look Once* (YOLO) family, renowned for their optimal speed-accuracy trade-off, have become particularly prevalent for this task [13, 28]. Their efficiency makes them suitable for near-real-time analysis on edge gateways or cloud servers, fulfilling the *real-time* requirement imposed by actionable IoT systems [29, 30]. Studies have successfully implemented versions from YOLOv4 to the latest YOLOv8 for detecting weeds in crops such as wheat, carrots, and soybeans, often reporting high accuracy [31, 32, 33].Despite technological progress, the development of robust, deployable systems faces persistent challenges that are often systemic in nature:

- **The Data Bottleneck:** Performance is intrinsically linked to training data. Research consistently highlights that dataset quality encompassing image resolution, lighting variance, and annotation precision is a critical, yet often undervalued, factor that can outweigh the benefits of larger, noisier datasets [15, 16, 34]. Furthermore, creating large, accurately annotated datasets remains expensive and time-consuming, a significant barrier to practical implementation [35, 36].
- **The Generalization Gap:** A model trained in one specific context (e.g., a particular field, crop stage, or lighting condition) frequently experiences a severe performance drop when deployed in a slightly different environment. This lack of robustness limits the scalability and practical utility of otherwise high-performing models [37, 38].

- **The Edge-Cloud Dichotomy:** A fundamental design choice in IoT systems is determining where processing occurs. Cloud computing offers vast power for model training but introduces latency and bandwidth dependency. Edge processing on drones or robots minimizes latency but is constrained by limited computational resources and power [39, 40].

Research Gap and Position of This Work
The literature reveals a focused trajectory: algorithmic refinement within the Processing Layer [14, 41]. While incremental improvements in model architecture (e.g., from YOLOv7 to YOLOv8) are valuable, a critical, system-level perspective is frequently absent. There is a pronounced lack of empirical studies that systematically isolate and evaluate the impact of Perception Layer attributes specifically, the intrinsic quality of captured image data on the overall performance of the IoT system. Most comparisons focus on model variants rather than data characteristics.This work addresses this gap. We position our study not merely as another application of YOLOv8, but as a systemic investigation into a key IoT design parameter. By implementing a standardized YOLOv8 pipeline within a simulated IoT workflow and conducting a controlled experiment comparing high-quality versus high-quantity datasets, we provide empirical evidence on a fundamental question: For an IoT-based weed detection system, is investing in superior data quality at the Perception Layer a more effective strategy than merely amassing larger volumes of data? Our findings aim to inform the design principles of future robust and efficient smart farming systems.

3. Background

A typical IoT system in smart agriculture is structured in layers, each with a distinct function [5, 18]. This work aligns with a five-layer conceptual model:

- **Perception Layer:** This is the physical interface with the environment, consisting of sensors and devices that capture data. In our context, this layer is represented by the UAV (drone) equipped with an RGB camera, responsible for image acquisition.
- **Network/Transport Layer:** This layer handles the communication and transmission of raw data from the perception devices to the processing units. While our experimental setup simulates this transfer, real-world deployments would utilize wireless protocols (e.g., Wi-Fi, 4G/5G, ZigBee, BlueTooth).
- **Processing Layer:** This is the "intelligence" core where data is stored, analyzed, and transformed into actionable information. In this study, this layer is embodied by the cloud-based Google Colab environment where the YOLOv8 model is trained and executes the weed detection algorithm on the received images.
- **Application Layer:** This layer presents the results to the end-user and enables decision-making or automated actions. Here, the output consists of the processed images with bounding boxes around detected weeds, which could be delivered via a farmer's dashboard or directly to an automated spraying system.
- **Business layer:** focuses on data interpretation, decision-making, and monetization of IoT services. It transforms raw data into actionable insights using AI and analytics, defines business models and strategies**,** ensures regulatory compliance and enhances user experience through dashboards and applications.

This layered abstraction provides a clear framework for understanding the flow of information and the placement of our experimental components within a full-scale smart farming system.

The YOLOv8 Object Detection Model
You Only Look Once version 8 (YOLOv8), developed by Ultralytics, is a state-of-the-art object detection model from the YOLO family [42]. It is designed for high speed and accuracy, making it particularly suitable for real-time applications common in IoT and edge-computing scenarios. Its architecture typically consists of:

- **Backbone** (e.g., CSPDarknet) for feature extraction from the input image.
- **Neck** (e.g., a Path Aggregation Network - PANet) for feature aggregation from different backbone stages, crucial for detecting objects at various scales.
- **Head** that performs the final detection, predicting bounding boxes, associated class probabilities (weed/background), and objectness scores.

For this study, we employed the YOLOv8n variant, which is the smallest and fastest in the series. This choice is motivated by its lower computational footprint, which aligns with potential future deployment on resource-constrained edge devices within an IoT ecosystem, without initially compromising on the representative power of a modern detection framework.

4. Proposed model and methodology

Our methodology simulates a streamlined IoT pipeline for weed detection, focusing on the Perception and Processing layers. The process, illustrated in Figure 1, follows these stages:

- **Data Acquisition (Perception Layer):** Image datasets are collected, simulating the output of a UAV-based scouting mission.
- **Data Preparation & Annotation:** The raw images are annotated to create ground truth for model training.
- **Model Training & Processing (Processing Layer):** The annotated data is used to train the YOLOv8n detection model in a cloud-simulated environment (Google Colab).
- **Inference & Evaluation:** The trained model is evaluated on unseen data, and its predictions (bounding boxes) are analyzed. The output represents the actionable information that would be delivered to the Application Layer.

To empirically study the effect of data quality versus quantity, two distinct datasets were curated:

- **Dataset D1 (High Quality):** Comprises 512 training images and 60 testing images of wheat fields. This dataset is characterized by high visual clarity, good contrast, and well-defined weed targets against the soil and crop background.
- **Dataset D2 (Higher Quantity, Lower Quality):** Comprises 5,061 training images and 241 testing images of a grass/weed environment. While larger in volume, this dataset exhibits lower overall image quality, with issues such as poorer resolution, motion blur, higher occlusion, and less optimal lighting conditions, making the weeds more challenging to identify.

Annotation: All images from both datasets were annotated at the object level using the Computer Vision Annotation Tool (CVAT). Bounding boxes were drawn around each visible weed instance. The annotations were exported in the YOLO format, where each image has a corresponding text file containing the normalized coordinates (center_x, center_y, width, height) for every bounding box.

- **Processing Layer: YOLOv8n Training and Inference Pipeline**
  A standardized deep learning pipeline was implemented using the Ultralytics library to ensure a fair comparison, where the only variable was the input training data.
- **Model Configuration:** The YOLOv8n model was initialized with its default architecture. The training hyperparameters were set as follows: number of epochs=100, image size imgsz=640, and a batch size determined by the framework's auto-batching for the available GPU memory. Crucially, data augmentation was explicitly disabled to isolate the effect of the original dataset quality without synthetic alterations.
- **Training Environment:** The model was trained from scratch (without pre-trained weights) on a Tesla T4 GPU provided by Google Colab. The Ultralytics YOLOv8 framework managed the training loop, loss calculation (based on a combination of classification, objectness, and bounding box regression losses), and optimizer steps (default: SGD).

Experimental Protocol for Isolating Data Impact
The core experiment was designed as a controlled comparison:

- Two separate instances of the YOLOv8n model were trained under identical configurations (architecture, hyperparameters, training environment).
- **Model A** was trained exclusively on **Dataset D1** (High Quality, n=512).
- **Model B** was trained exclusively on **Dataset D2** (Higher Quantity, n=5,061).
- Both models were evaluated on their respective, unseen test sets using the same comprehensive metrics.

This design directly tests the hypothesis that for weed detection in an IoT pipeline, the quality of data from the Perception Layer is a more critical performance factor than its sheer volume.

5. Evaluations and Results

Evaluation Metrics.
The models were evaluated on their respective hold-out test sets using standard object detection metrics:

- **Precision:** The proportion of correctly identified weeds among all predicted weeds (i.e., *What fraction of our alarms are correct?*).
- **Recall:** The proportion of actual weeds that were correctly detected by the model (i.e., *What fraction of all weeds did we find?*).
- **Mean Average Precision at IoU=0.5 (mAP@50):** The primary metric, representing the area under the Precision-Recall curve averaged over all classes at an Intersection-over-

Union threshold of 50%. This single score balances both precision and recall, providing a holistic view of detection accuracy.

Quantitative Results and Comparative Analysis
The performance of the two models is summarized in Table 1. The results demonstrate a clear and significant advantage for the model trained on the high-quality dataset **D1**, despite it being an order of magnitude smaller than **D2**.

Table 1: *Comparative performance on Dataset D1 (High Quality) vs. Dataset D2 (High Quantity).*

Dataset	Training Images	Precision	Recall	mAP@50
D1 (High Quality)	512	**0.88**	0.80	**0.90**
D2 (High Quantity)	5,061	0.74	0.77	0.82

Key Findings:

- **Superior Overall Accuracy:** The model trained on D1 achieved a mAP@50 of 0.90, substantially outperforming the model trained on D2 (mAP@50 of 0.82). This represents a 9.8% relative improvement in the primary detection metric.
- **Higher Precision:** The precision of the **D1** model (0.88) is markedly higher than that of the **D2** model (0.74). This indicates that the detections made by the high-quality data model are more reliable, resulting in fewer false positives. In a precision agriculture context, this translates to reduced risk of misapplying herbicides to crops or soil.
- **Comparable Recall:** Recall values are similar (0.80 vs. 0.77), suggesting both models are reasonably adept at finding weeds present in the images. The slight edge for **D1** indicates it misses fewer true weed instances.

Interpretation: These results provide strong empirical evidence that data quality is a more decisive factor for model performance than data quantity within this IoT-aligned detection framework. Investing in a smaller set of clear, well-defined images from the Perception Layer yields a more accurate and reliable detection system in the Processing Layer than amassing a large volume of lower-fidelity data.

Qualitative Analysis and Visual Observations
Visual inspection of the model predictions corroborates the quantitative findings.
Representative examples are shown in Figure 5 and Figure 6 (data samples), Figure 3 and Figure 4 (detection results).

Model trained on D1: Predictions are characterized by high-confidence bounding boxes that tightly fit the weed targets (Figure 3 and Figure 5). There are fewer instances of spurious detections on background elements or crop residues.

Model trained on D2: Predictions show more variability (Figure 4 and Figure 6). While it detects many weeds correctly, it also exhibits a higher frequency of false positives (marking soil clumps or shadows as weeds) and occasionally less accurate bounding box localization. This aligns with its lower precision score.This qualitative difference underscores that noise and ambiguity in the training data lead directly to ambiguity in the model's predictions, reducing its operational reliability.The experiment validates a critical system-level insight: Optimization must extend beyond the algorithm to encompass the entire data pipeline. For IoT-based smart agriculture systems:

- **Perception Layer Quality is Non-Negotiable:** Ensuring high-quality image capture (good resolution, stable platforms, optimal lighting) is a prerequisite for high-performing analytics.
- **Cost-Benefit of Data Curation:** The results suggest that the resource investment required to curate a smaller, high-quality dataset can yield a higher return in performance than the effort expended to collect and annotate a much larger but poorer-quality dataset.
- **Generalization vs. Specificity:** While a large, diverse dataset is the ideal for generalization, this study shows that in its absence, a smaller dataset of *high representative quality* for the target environment is a more effective starting point for building a functional system.

6. Conclusions

This study presented a holistic investigation into a key design parameter for IoT-enabled smart weed detection systems. Moving beyond isolated algorithmic improvements, we framed the problem within a layered IoT architecture and conducted a controlled experiment to evaluate the impact of Perception Layer data quality. Our main contributions are:

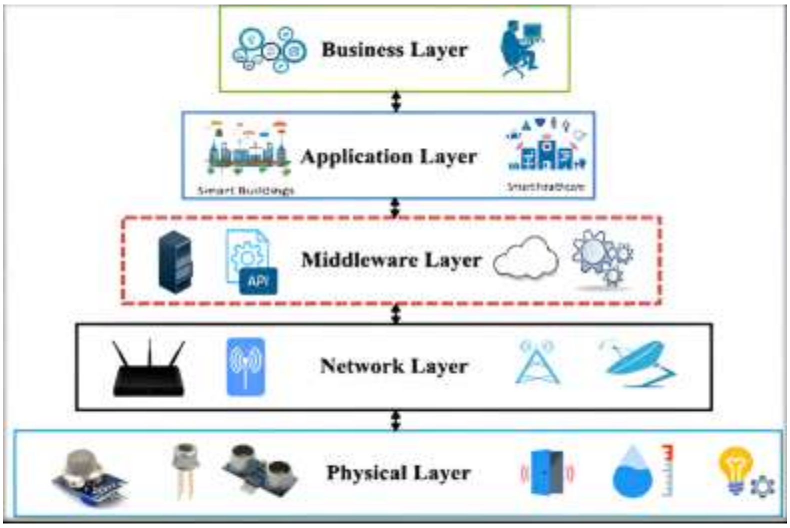

Figure 1 *The IOT architecture model*

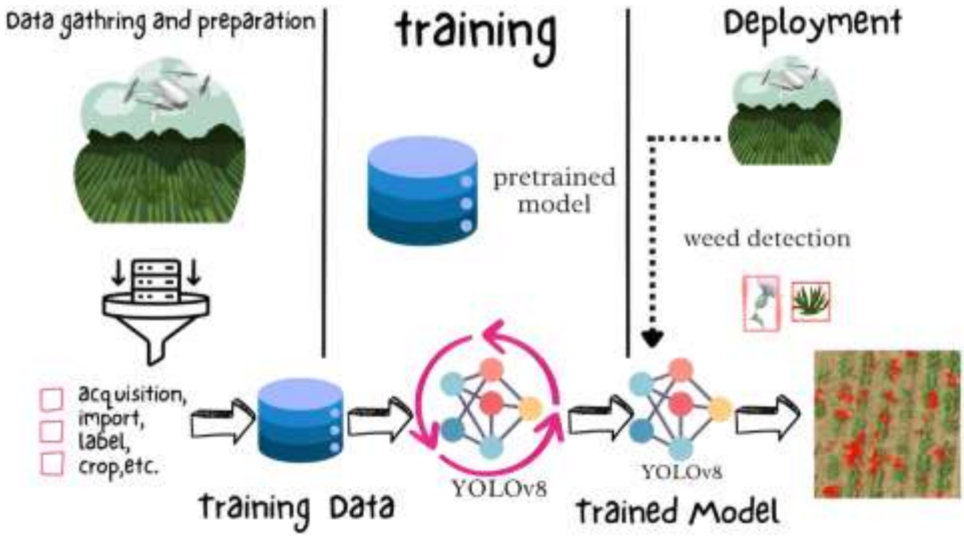

Figure 2. *The Model Architecture*

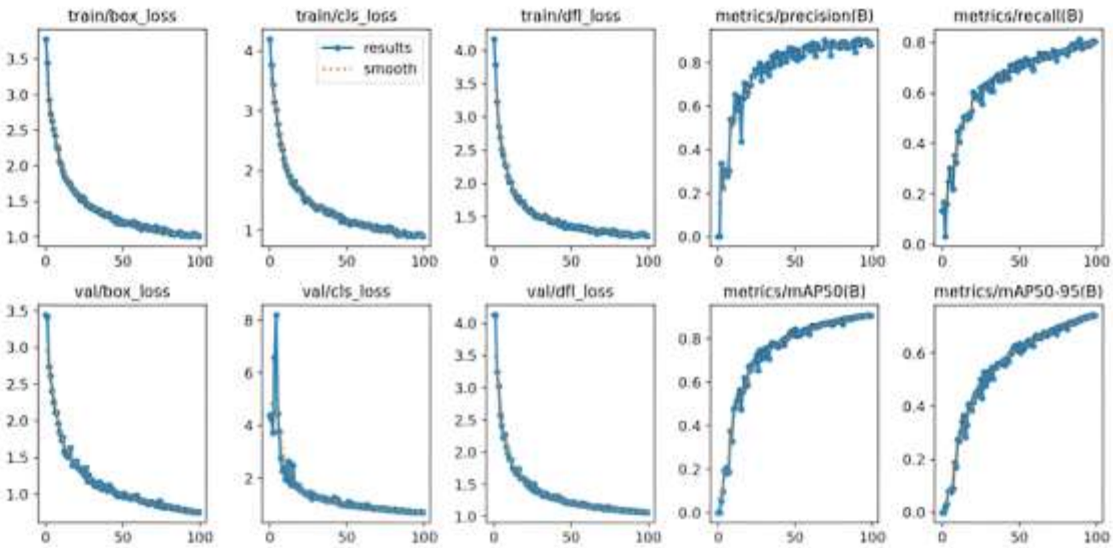

Figure 3. *Evaluation Metrics for Data set 1*

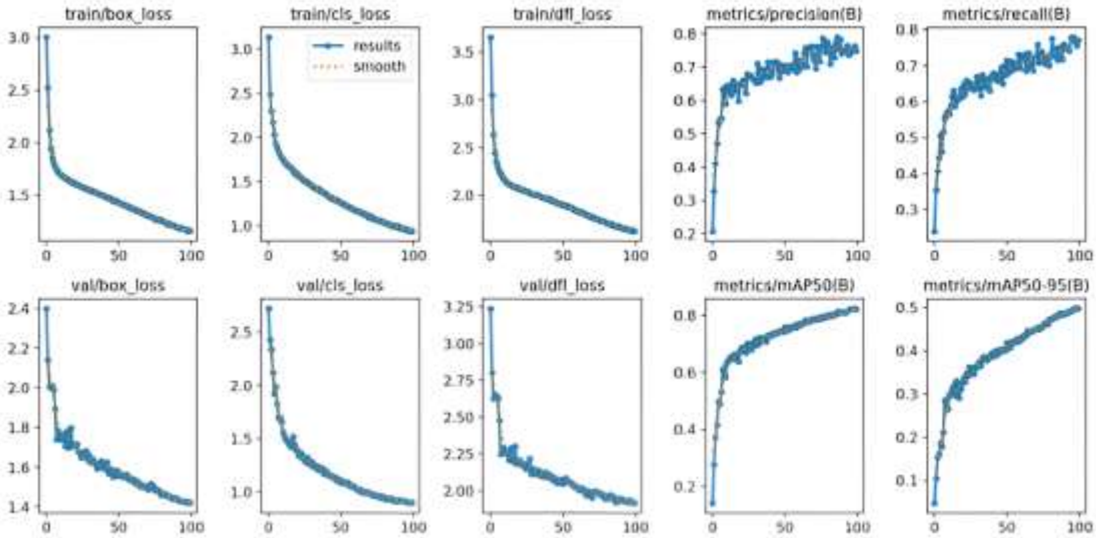

Figure 4. *Evaluation Metrics for Data set 2*

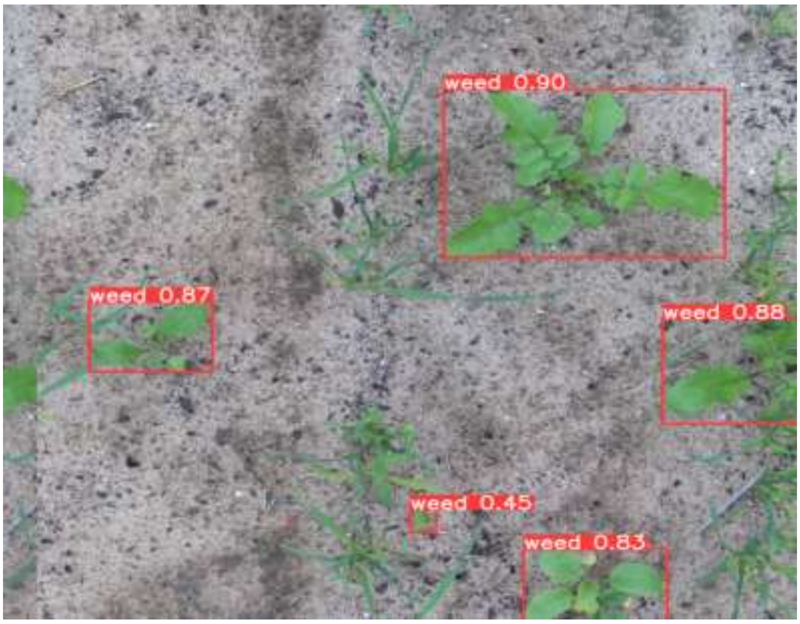

Figure 5. *Prediction results for data set 1*

Figure 6. *Prediction results for Data set 2*

- The development and documentation of a reproducible, IoT-aligned pipeline for weed detection using the state-of-the-art YOLOv8n model.
- Empirical evidence that the quality of training data is a more critical performance lever than its quantity. The model trained on a smaller (n=512) but high-quality dataset achieved a 0.90 mAP@50, significantly outperforming the model trained on a larger (n=5,061) but lower-quality dataset (0.82 mAP@50).
- A system-level recommendation for practitioners: prioritizing high-fidelity data acquisition and annotation is an essential and effective strategy for developing robust in-field detection systems.

This work has certain limitations that point to valuable future research directions:

- **Scope of Crops and Conditions:** The study was conducted on specific field datasets (wheat and mixed grass). Validation across a wider variety of crops (e.g., maize, vegetables) and more extreme environmental conditions is necessary.
- **Model Scale:** The experiment used the lightweight YOLOv8n variant. Future work should examine if the same quality-quantity relationship holds for larger, more parameter-rich models.
- **Advanced Learning Techniques:** To mitigate the data quality challenge, future work could explore **semi-supervised or self-supervised learning** techniques that leverage large amounts of unlabeled field imagery to improve model robustness and generalization [43].

Remarks

The convergence of IoT and AI holds immense promise for sustainable agriculture. This research underscores that realizing this promise requires a system-level perspective. By demonstrating that superior data quality from the sensor layer decisively enhances analytical outcomes, we provide a pragmatic guideline for building more effective and reliable smart farming solutions. The path forward lies in the co-design of robust sensing platforms and intelligent processing algorithms, ensuring that the intelligence infused into our fields is built upon a foundation of clear and trustworthy data.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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