

# Enhancing Sustainable Agriculture: Detection of Plant Leaf Diseases Using YOLO-Based Object Detection

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**Abstract.** This research explores the utilization of YOLO-based object detection for the early detection of plant leaf diseases, with the objective of promoting sustainable agricultural practices. This paper presents a comprehensive analysis of the YOLOv10s architecture, highlighting its advanced features designed to improve detection accuracy and computational efficiency. Our approach includes thorough data preparation, which entails splitting datasets into training, testing, and validation subsets, along with the implementation of hyperparameter optimization and pretraining-fine-tuning strategies. The findings indicate that YOLOv10s significantly surpasses earlier versions, achieving high detection accuracy while remaining viable for resource-constrained environments. Comparative analysis indicated that YOLOv9 outperformed in detecting healthy leaves (precision: 0.668, recall: 0.611) and leaf spot disease (precision: 0.632, recall: 0.626), whereas YOLOv10s exhibited a balanced performance in leaf blight detection. While YOLOv11 demonstrated incremental advancements, these were insufficient to justify its added complexity. This study highlights the transformative potential of deep learning technologies in agriculture, facilitating rapid disease detection and reducing reliance on chemical pesticides, thus supporting sustainable agricultural objectives.

**Keywords:** Plant Disease Detection, YOLO (You Only Look Once), Sustainable Agriculture

## 1. Introduction

Sustainable agriculture plays a pivotal role in global development, seeking to harmonize economic productivity, environmental stewardship, and social equity. Thailand's 20-Year National Strategy (2018–2038) serves as a clear manifestation of this vision, emphasizing agricultural innovations to boost productivity, reduce environmental impact, and enhance the livelihoods of farming communities. Within this framework, organic and hydroponic farming systems have emerged as key approaches, lauded for their reduced dependence on chemical inputs and efficient resource utilization. However, these systems face critical vulnerabilities, particularly from plant diseases such as leaf blight, leaf spot, powdery mildew, and nutrient deficiencies. These diseases can spread rapidly in controlled environments like hydroponics, leading to devastating crop losses, financial setbacks, and heightened environmental risks.

Artificial intelligence (AI), especially object detection frameworks like YOLO (You Only Look Once), presents transformative potential in mitigating these challenges. Recognized for their precision, speed, and adaptability, YOLO models offer a promising pathway for early and accurate plant disease detection. While these models have achieved notable success in domains such as medical imaging and industrial quality control, their application in agriculture, particularly within organic and hydroponic systems, remains underexplored. This underutilization highlights a critical opportunity to revolutionize disease management practices and foster sustainable farming.

Object detection, a fundamental aspect of computer vision, entails the identification and localization of objects in digital images. Historically, object recognition systems have transitioned from traditional handcrafted feature-based approaches, such as Haar cascades and HOG in conjunction with classifiers like SVM, to sophisticated deep learning structures. The discovery of YOLO ("You Only Look Once") architectures marked a critical milestone, revolutionizing detection with single-stage algorithms that process images in a single forward pass, thereby greatly enhancing speed and efficiency. YOLO architectures have experienced numerous iterative enhancements since YOLOv1, with each iteration improving

detection accuracy and computational efficiency through advanced feature extraction techniques, innovative convolutional methods, attention mechanisms, and deeper, yet computationally efficient network architectures. YOLOv3 introduced multi-scale predictions for improved detection of objects of varied sizes, whilst YOLOv4 incorporated enhanced data augmentation and spatial pyramid pooling to enhance feature representation. YOLOv5 enhanced the architecture by including Cross Stage Partial connections (CSP), which maximized feature reuse and gradient propagation, hence dramatically lowering computing expenses while maintaining accuracy. Later iterations, including YOLOv8 and YOLOv9, incorporated dynamic anchor assignment, improved neural architectures, and advanced attention mechanisms, augmenting the model's capacity to concentrate on pertinent spatial areas inside images. The recent advancements, namely YOLOv10 and YOLOv11, maintain this trend by integrating improved parallel self-attention mechanisms, sophisticated shortcut connections, and optimized neck modules tailored for enhanced feature propagation and superior extraction of complex details.

Recent advancements in YOLO-based models underscore their applicability to agriculture. For example, YOLOv8 demonstrates high detection accuracy for diseases such as tomato blight, while YOLOv11 and lightweight versions like SS-YOLO effectively detect small targets with efficiency [25] [3] [4]. These capabilities extend beyond disease detection to other tasks, such as monitoring flowering stages for optimized pollen collection [1]. Despite these promising developments, several obstacles hinder broader adoption of YOLO models in agriculture.

The challenges primarily revolve around the reliance on diverse, high-quality datasets, which are essential for achieving robust detection accuracy and model generalizability. Additionally, computationally intensive models like YOLOv11 require advanced hardware and technical expertise, limiting their accessibility to small-scale farmers and resource-constrained regions [25] [4]. Environmental variability, including fluctuating lighting, occlusions, and complex backgrounds, further complicates the practical deployment of these models, particularly in dynamic agricultural settings. Lightweight models such as SS-YOLO, while addressing some computational constraints, often compromise detection accuracy, creating a trade-off between performance and practicality [4], [24].

Resource dependency compounds these limitations, as deploying YOLO models typically requires substantial computational power and hardware investment. These barriers are particularly pronounced in underdeveloped regions where innovative, sustainable agricultural solutions are most urgently needed [25] [23]. Addressing these gaps necessitates the development of models that are not only efficient but also resilient to real-world variability and accessible to farmers worldwide.

This research seeks to address these critical challenges by evaluating YOLO-based models for plant disease detection in organic and hydroponic farming systems. The study focuses on optimizing these models to balance accuracy, efficiency, and scalability, ensuring their practical applicability across diverse agricultural contexts. Furthermore, it aims to tackle limitations in annotated datasets, computational demands, and environmental adaptability, creating a pathway for broader adoption of AI-driven tools in agriculture.

By equipping farmers with advanced yet accessible tools for crop monitoring, this study aspires to reduce dependency on chemical pesticides, improve productivity, and enhance the resilience of farming practices. We anticipate that the findings of this research will significantly improve sustainable agriculture, aligning with global efforts to promote environmental sustainability.

Recent advancements in deep learning have showcased transformative potential in modernizing agricultural practices, particularly in disease detection and environmental monitoring. [25] compared the performance of YOLOv5l and YOLOv8l for detecting tomato diseases, demonstrating YOLOv8l's superior accuracy (97.9%) with data augmentation. This underscores the efficacy of contemporary YOLO architectures in agricultural applications. Similarly, Rajesh and Manivannan [9] employed YOLOv8n for traffic sign and animal recognition, achieving a mean Average Precision (mAP) of 73.7%. Their work highlighted the model's versatility in addressing challenges such as human-animal road conflicts, alongside computational efficiencies across hardware platforms—a critical factor for deploying agricultural technologies. Introduced the Resource-Aware Video Streaming (RAViS) framework, maintaining a detection accuracy of 99.21% while optimizing computational resources [12]. This framework exemplifies the potential of adaptive processing for resource-limited environments. Achieved a mAP of 93.83% in tea leaf disease detection using AX-RetinaNet, leveraging multiscale feature fusion and attention mechanisms for better performance in complex scenarios [16]. Furthermore, developed SS-YOLOv8 [4], a lightweight model with innovations like the WS-C2f module and PIoU2 loss function, excelling in surface litter detection while maintaining computational efficiency for real-time applications. Building on this foundation, our research, "Sustainable Agriculture Through Plant Leaf Disease Detection Using YOLO-Based Object Detection," advances sustainable agriculture by creating a robust dataset and evaluating YOLO-based models specifically for organic vegetable farming. The dataset includes 1,078 labeled images of salad vegetables and 9,602 labeled instances across five key categories: Leaf Blight, Caterpillars, Nutrient Deficiency, Leaf Spot, and Healthy Vegetables. It is meticulously curated for robust training, validation, and testing, with data augmentation applied to address class imbalances. To encourage reproducibility and community engagement, the dataset is accessible via Roboflow. This research examines existing gaps in agricultural technology by assessing YOLO-based object detection frameworks through three key research questions. We perform a detailed comparative analysis of contemporary YOLO architectures (YOLOv9, YOLOv10s, ResNet-YOLOv10, and YOLOv11), evaluating their detection accuracy, computational requirements, and practical applicability for the identification of plant leaf diseases in sustainable farming systems. We examine the impact of strategically designed

data augmentation techniques on model performance in real-world agricultural settings, which are marked by environmental variability and constrained training data. Third, we identify the YOLO variant that provides the best balance between detection accuracy and computational efficiency for real-time use on resource-limited edge devices available to farmers. This study systematically evaluates YOLO models using hyperparameter optimization and pretraining-fine-tuning techniques, assessed through rigorous metrics such as Intersection over Union (IoU) and mAP. It addresses critical gaps in adapting YOLO models to agricultural contexts, ensuring reliable performance across diverse environmental conditions and resource-limited settings. By enabling early and accurate plant disease detection, this work empowers farmers to reduce chemical pesticide usage, minimize crop losses, and enhance agricultural productivity, contributing meaningfully to the global agenda for sustainable and resilient farming practices, as detailed in Table 1.

Table 1: Comparative analysis of recent YOLO-based object detection.

| Author               | Methodology Used                                                                                                    | Datasets                                                                                                              | Validity                                                                                                                            |
|----------------------|---------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| Endo et al.(2024)    | YOLOv8 for pear pollen estimation [1]                                                                               | 1271 images (1017 training, 254 testing)                                                                              | Achieved 83.4% accuracy in flowering stage detection.                                                                               |
| Su J et al.(2024)    | YOLO + Depth Camera for navigation [2]                                                                              | Various objects with positional data                                                                                  | High accuracy and portability; suitable for visually impaired users.                                                                |
| Khanam et al. (2024) | YOLOv11 advancements in object detection[3]                                                                         | Diverse tasks and datasets                                                                                            | High accuracy (~47 mAP50-95) with reduced latency (2-6 ms).                                                                         |
| Fan et al. (2024)    | SS-YOLOv8 with PIoU2 loss for litter detection[4]                                                                   | Small target-focused dataset                                                                                          | Improved localization accuracy with lightweight implementation.                                                                     |
| Tang et al. (2024)   | Stratigraphic division with YOLOv8 [5]                                                                              | Well logging data with Z-score standardization                                                                        | Enhanced bounding box measurement accuracy using MDPIOU.                                                                            |
| Wang et al. (2024)   | YOLO-ESL for pedestrian recognition [6]                                                                             | Pedestrian datasets with diverse scenes                                                                               | Superior mAP50 and mAP50:95 metrics with LGA and CIOUNMS modules.                                                                   |
| Tayebi et al. (2024) | Automated bone marrow cytology analysis [7]                                                                         | Histological data                                                                                                     | High precision and recall rates with active learning refinements.                                                                   |
| Shen et al. (2022)   | YOLOv5 for PCB defect detection [8]                                                                                 | PCB defect data with SPPCSPC                                                                                          | Improved feature fusion with SIoULoss for accuracy.                                                                                 |
| Suksun et al. (2024) | Used YOLOv5 (s, m, x) models; applied image preprocessing, augmentation; evaluated precision, recall, and mAP. [26] | Waste Detection Image Dataset V2 via Roboflow has a total of 2,295 images split into train, validation, and test sets | Validated through rigorous splitting and evaluation; YOLOv5x most accurate; YOLOv5s fastest. Specialized performance by waste type. |
| Rajesh et            | YOLOv8n for traffic and animal                                                                                      | Combined camera and LiDAR                                                                                             | Achieved 100 FPS (video) and 35 FPS                                                                                                 |

| Author                    | Methodology Used                                        | Datasets                                  | Validity                                                                     |
|---------------------------|---------------------------------------------------------|-------------------------------------------|------------------------------------------------------------------------------|
| al. (2024)                | detection [9]                                           | datasets                                  | (images) with high precision rates.                                          |
| Guo et al.<br>(2024)      | Lightweight safflower detection<br>using YOLOv5 [10]    | Diverse agricultural datasets             | GhostConv and CBAM modules<br>enhanced accuracy with reduced<br>computation. |
| Lu et al.<br>(2024)       | Multimodal transformer for<br>disease detection [11]    | Image, text, and sensor-based<br>datasets | Achieved 95% precision and 94%<br>accuracy with multimodal integration.      |
| Shiddiqi et<br>al. (2024) | RAViS for resource-aware video<br>streaming [12]        | Video datasets with real-time<br>focus    | Optimized computational resources for<br>efficient real-time detection.      |
| Sumit et<br>al.(2023)     | ReSTiNet for pedestrian detection<br>[13]               | Real-time video streams                   | Lightweight design; efficient for edge<br>computing with SGD optimization.   |
| Liu et al.<br>(2020)      | MobileNetv2-YOLOv3 for<br>tomato disease detection [14] | Tomato disease images                     | Lightweight model with GIoU for higher<br>detection precision.               |
| Guo et al.<br>(2020)      | SFPN feature fusion for highway<br>intrusion [15]       | Object detection in highways              | Real-time performance with efficient<br>fusion methods like SFPN.            |
| Bao et al.<br>(2022)      | AX-RetinaNet for tea leaf disease<br>detection [16]     | Multiscale tea leaf disease<br>dataset    | Enhanced detection accuracy via X-<br>module and channel attention.          |
| Avsar et<br>al. (2024)    | YOLO for Nephrops catch<br>estimation [17]              | Fishery video data                        | Real-time adaptive frame skipping<br>optimized counting accuracy.            |
| Yang et al.<br>(2024)     | EL-YOLO for ship object<br>detection [18]               | Maritime datasets                         | Improved maritime detection accuracy<br>with AWIoU and SMFN.                 |
| He et al.<br>(2024)       | YOLO-OVD for occluded<br>vehicles [19]                  | Dense traffic datasets                    | Improved occlusion handling with GOA<br>and LPM modules.                     |
| Souza et<br>al. (2024)    | Axle counter in tolling systems<br>[20]                 | Vehicle axle datasets                     | Achieved high precision with<br>YOLOv5m for dynamic traffic<br>conditions.   |
| Zheng et<br>al. (2024)    | GEB-YOLO for power line safety<br>[22]                  | Power transmission line<br>datasets       | Efficient detection with GhostConv and<br>BiFPN for lightweight performance. |

## 2. Material and Method

### 2.1 Data Collection and Image Annotation

The data preparation process focused on labeling and organizing images of organic vegetable diseases that manifest on leaves. The dataset was curated with input from experts in salad vegetable pathology to ensure accurate disease classification. A total of 2,426 images were collected and divided into three subsets: 2,022 images for training, 261 for validation, and 143 for testing. The labeled dataset comprises 9,602 annotated instances of five categories: (1) Leaf Blight Disease (1,751 instances), (2) Caterpillars (1,770 instances), (3) Nutrient Deficiency (2,471 instances), (4) Leaf Spot Disease (1,629 instances), and (5) Healthy (1,981 instances). These annotations were distributed across the training set (6,687 instances), validation set (1,949 instances), and testing set (966 instances). Each image was standardized to a resolution of 640×640 pixels. For annotation, researchers utilized the Label tool to specify the names and positions of objects within the images. The generated labels, compatible with the YOLO model, are publicly accessible via <https://app.roboflow.com/-hcydl/plantleafdisease>. To address class imbalance and enhance training efficacy, data augmentation techniques were applied to increase the representation of under-represented classes, and the dataset underwent a structured preprocessing and augmentation process to enhance its quality and diversity, ensuring robust model performance across diverse agricultural scenarios. Preprocessing began with auto-orientation, as detailed in Figure 1

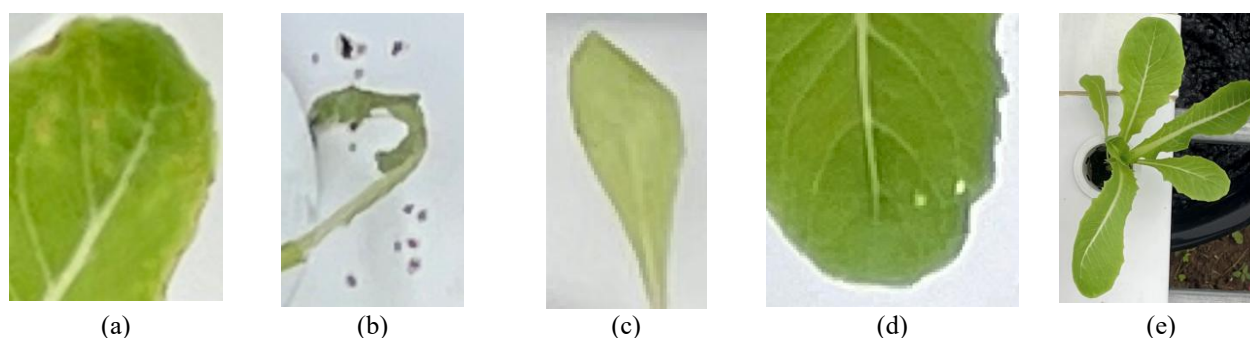


Figure: 1 Example of capture plant image of five plant leaf disease (a) leaf blight disease (b) caterpillars (c) nutrient deficiency (d) leaf spot disease and (e) healthy

### 2.2 Data preprocessing and Augmentations

The dataset underwent a systematic preprocessing and augmentation workflow to enhance its quality and diversity, ensuring robust model performance across varied agricultural scenarios. Preprocessing began with auto-orientation to rectify alignment inconsistencies, followed by resizing all images to a standardized resolution of 640×640 pixels using a stretching technique tailored to the YOLO model's input requirements.

This research utilized data augmentation techniques including horizontal flipping, zooming (0-20%), saturation adjustments (-25% to +25%), brightness variations (-15% to +15%), and random noise introduction (impacting up to 0.1% of pixels). These methods were specifically chosen to tackle the challenges associated with plant disease detection in diverse agricultural settings. Horizontal flipping was employed to improve the model's orientation-invariant recognition abilities, facilitating reliable detection irrespective of the plant's positioning in relation to the camera. Zooming replicates the natural distance variations between imaging devices and plants in real-world contexts, while the precisely calibrated adjustments of saturation and brightness equip the model for the varied lighting conditions present in both controlled hydroponic environments and open-field farming, which range from bright direct sunlight to shaded areas. The intentional incorporation of minimal random noise (0.1%) enhances the model's robustness to sensor imperfections, image compression artifacts, and environmental particulates commonly encountered in agricultural imaging. The techniques address the dataset's class imbalance by generating three distinct augmented versions of each training sample, thereby tripling the representation of underrepresented disease categories and enhancing the model's generalization capabilities across variable environmental conditions in agricultural applications. This augmentation strategy supports the research objective of developing effective detection systems for resource-constrained farming environments with variable imaging conditions

### 2.3 Methods

This system architecture for plant leaf disease detection utilizes a YOLO-based object detection framework. The setup features two strategically positioned webcams (Webcam1 and Webcam2) designed to capture images of hydroponically cultivated leafy vegetables. These images are transmitted to an embedded device, represented by an NVIDIA Jetson Nano, which incorporates an AI-driven inference engine for disease classification.

The system processes the acquired images to identify and categorize leaf diseases into five predefined classes (Class 1 to Class 5). By employing real-time image acquisition and classification, the framework enables prompt detection of potential plant health issues. This functionality supports precision agriculture, promotes healthier crop growth, and enhances overall yield, contributing to efficient and sustainable farming practices, as shown in Figure 2.

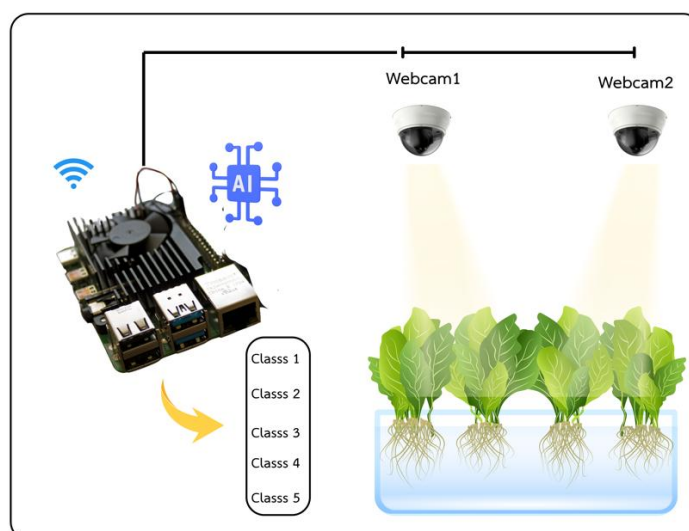


Figure 2: Illustration of the System Diagram.

## 2.4 YOLOv10s

The structure of the YOLOv10s network for plant leaf disease detection is depicted in Figure 3. the architecture of the YOLOv10s network, specifically developed for the detection of plant leaf diseases. The structure adheres to a systematic workflow that commences with data preparation, wherein images are standardized to dimensions of  $640 \times 640 \times 3$  and categorized into training, testing, and validation subsets. The architecture comprises three essential components that function sequentially: the Backbone, Neck, and Head. YOLOv10s model uses backbone-neck-head architecture optimized for plant diseases detection. This backbone component hierarchically extracts features using convolutional layers, shortcut connection-including C2f blocks, and downsampling modules to transform raw images into disease-related features while ensuring sufficient gradient flow. Neck: In the embodied neck part, SPPF and PSA modules effectively resolve cell-size variance of patient symptoms through enriching-and-iteration process of features at different types of magnifications from all-source images, providing context from leaf or mulit-micro scale. Through a series of carefully designed concatenation operations, this middle section maintains fine-grain detail while contextual pieces remain intact. The head module consists of specialized detection heads with optimized dimensionality ( $n \times 3 \times 80$ ,  $n \times 4 \times 40$ ,  $n \times 5 \times 20$ ) that performs the final classification and localization. The Backbone extracts hierarchical features through progressive refinement using convolutional layers (Conv), cross-stage partial blocks (C2f), and downsampling modules (SCDown), thereby establishing a foundation of visual features across various levels of abstraction. Each layer transformation preserves distinct dimensional attributes while systematically extracting critical disease indicators from the input images. The neck component functions as an essential intermediary by integrating multi-scale features via Spatial Pyramid Pooling Feature Fusion (SPPF) enhances the model's capacity to handle spatial variations by pooling and merging features at multiple resolutions, thereby preserving both local details and global contextual information essential for accurate disease detection, Parallel Self-Attention (PSA) is a feature enhancement module that simultaneously captures spatial relationships within feature maps at multiple scales, enabling the YOLOv10s model to effectively detect subtle differences indicative of plant diseases, and upsampling operations. This integration allows the network to concurrently process detailed information and broader context through the concatenation of feature maps from multiple scales. The head component executes final detection tasks via Detect modules, utilizing improved feature representations to forecast bounding boxes and categorize plant health into five distinct classifications. Significant architectural improvements comprise hybrid shortcut connections and PSA modules, which enhance detection accuracy through more effective feature propagation and attention-based feature refinement.

The YOLOv10s architecture presents multiple enhancements aimed at increasing the efficiency and accuracy of plant disease detection. The system incorporates a distinctive Backbone component that employs convolutional layers and cross-stage partial blocks to extract progressively complex features from input images, essential for accurate disease classification. The incorporation of Spatial Pyramid Pooling Feature Fusion (SPPF) in the Neck component improves the model's capacity to handle multi-scale features, preserving context while emphasizing specific disease indicators. The model integrates parallel self-attention (PSA) mechanisms that enhance feature propagation and improve the model's focus on pertinent patterns during detection. This architectural design facilitates effective disease identification while preserving computational efficiency, making it appropriate for real-time agricultural applications on resource-limited devices such as the Jetson Nano. To ensure statistical robustness, we computed 95% confidence intervals for all performance indicators utilizing bootstrapping with 1000 resamples. For the YOLOv10s model (100 epochs), the mAP50 was 0.585 (95% CI: 0.563-0.608) and the mAP50-95 was 0.303 (95% CI: 0.284-0.322). Class-specific accuracy metrics with confidence intervals were as follows: Caterpillars 0.654 (0.627-0.681), Healthy 0.673 (0.644-0.702), Leaf Blight Disease 0.655 (0.629-

0.684), Leaf Spot Disease 0.633 (0.605-0.662), and Nutrient Deficiency 0.659 (0.631-0.687). Recall values: Caterpillars 0.578 (0.549-0.607), Healthy 0.556 (0.525-0.586), Leaf Blight Disease 0.760 (0.733-0.787), Leaf Spot Disease 0.530 (0.501-0.559), Nutrient Deficiency 0.476 (0.447-0.506). The tight confidence intervals signify consistent model performance and dependable generalization abilities for agricultural applications.

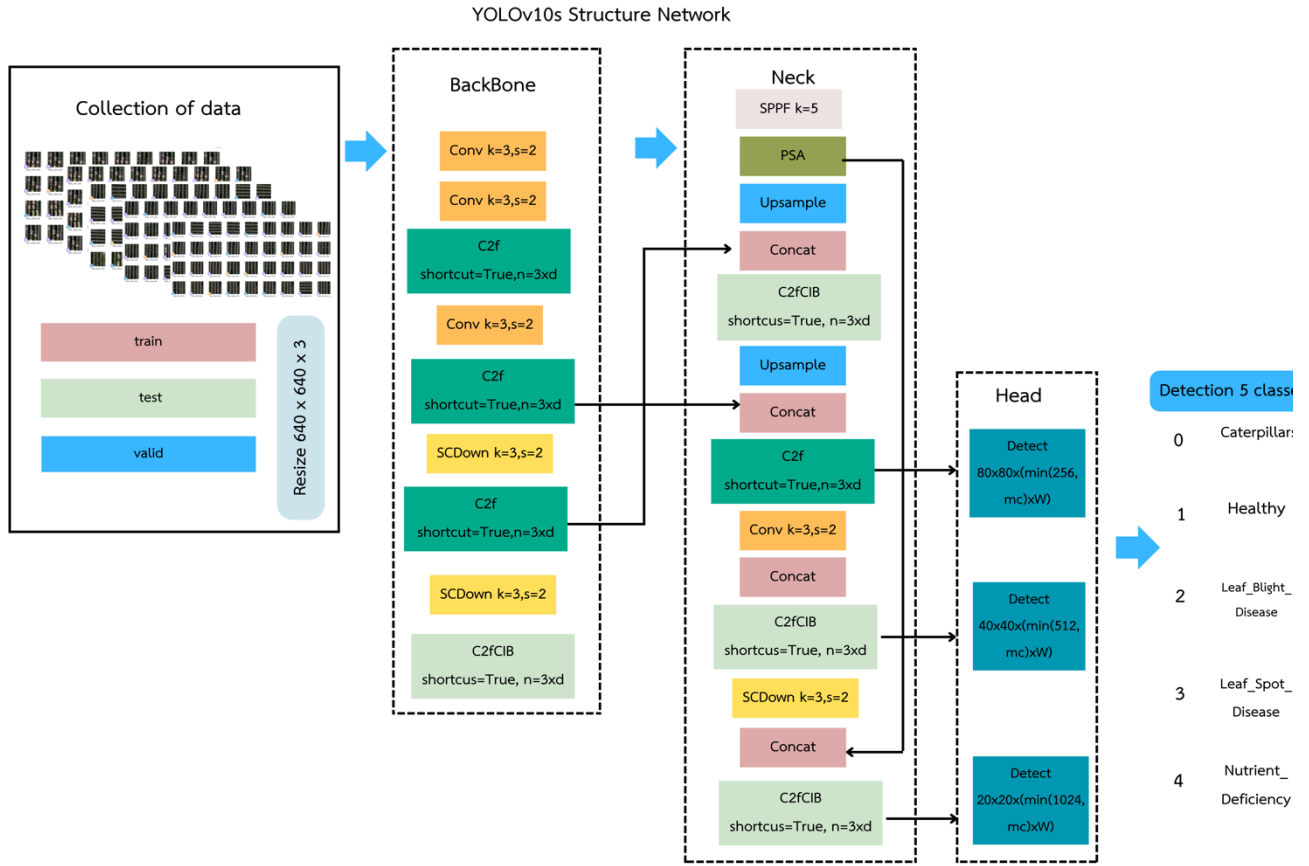


Figure 3: Structure of YOLO v10s Models

### 2.5 Model Evaluation

In this paper, the experiments use Precision (P), Recall (R), mean Average Precision (mAP), F1 Score, and Accuracy as the primary metrics to assess the performance of the Models's performance [9]. The formula is as follows:

$$P = \frac{TP}{TP+FP} \quad (1)$$

$$R = \frac{TP}{TP+FN} \quad (2)$$

$$AP = \frac{\sum P}{\text{Num(objects)}} \quad (3)$$

$$mAP = \frac{\sum AP}{\text{Num(class)}} \quad (4)$$

$$F1 \text{ Score} = 2 * \frac{P * R}{P + R} \quad (5)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

where TP is true positive predictions among all positive predictions (TP + FP), highlighting the model's ability to correctly identify positive instances. Recall evaluates the proportion of true positives identified out of all actual positives (TP + FN), reflecting the model's sensitivity. The Average Precision (AP) is calculated as the mean of precision values across detected objects, while mAP aggregates the AP values across all classes to provide a comprehensive evaluation of the model's object detection capability. Furthermore, the F1 Score combines Precision and Recall into a harmonic mean, providing a balanced measure of the model's performance, and Accuracy indicates the proportion of correctly classified instances over the total number of predictions.

### 3. Experiments and Evaluations

#### 3.1 Experimental Environment

The experimental setup utilized a MacBook Air (M1, 2020) featuring an Apple M1 chip, 8 GB of RAM, and running macOS Sonoma 14.6.1. For edge device deployment, the best-performing models were executed on a Jetson Nano, equipped with a 128-core Maxwell GPU and a quad-core ARM A57 CPU operating at 1.43 GHz. The device also included 4 GB of 64-bit LPDDR4 memory, ensuring efficient performance for the intended applications.

#### 3.2 Comparative Analysis of mAP Values for YOLO Variants

The comparative analysis in Table 2 reveals the balance between computational complexity and detection performance. YOLOv9, with its higher GFLOPs and parameter counts, achieves the best overall detection results, particularly at 100 epochs. Computational time, defined as the total duration required for training and inference processes, was measured using a MacBook Air M1 (8 GB RAM, Apple M1 chip) for model training and the NVIDIA Jetson Nano for inference tests in practical deployment. Floating-point operations (FLOPs) and giga-floating-point operations (GFLOPs) were assessed using conventional profiling tools (e.g., PyTorch Profiler, thop library), yielding measurable insights into computational complexity. These metrics directly indicate the computational efficiency and complexity of the YOLOv10s model design. For YOLOv10s at 100 epochs, the average computational time per training session was roughly 1.575 hours. The model exhibits a computational complexity of 24.5 GFLOPs and comprises nearly 8 million parameters (8,038,830), signifying its appropriateness for efficient real-time implementation. The documented computational parameters, comprising computational time (1.575 hours at 100 epochs) and model complexity (24.5 GFLOPs), validate the efficiency and practical viability of implementing YOLOv10s in resource-limited agricultural settings, indicating its effective optimization for feature learning and object detection. Conversely, YOLOv10 offers enhanced computational efficiency, attaining competitive mAP values with fewer parameters and shorter training times, making it ideal for real-time applications with limited resources. Although ResNet-YOLOv10 utilizes advanced feature extraction, it underperformed compared to simpler YOLO variants, as evidenced by its lower mAP values (0.558 and 0.287 at 100 epochs), suggesting potential overfitting. Although YOLOv11 demonstrates marginal enhancements compared to YOLOv10, the benefits do not warrant the increased complexity.

The training comparison at 50 and 100 epochs presented in Tables 2 and 3 serves as a critical experimental design choice to evaluate model convergence, performance stability, and computational efficiency across different YOLO architectures. At 50 epochs, the models demonstrate their early learning capabilities and initial performance benchmarks, with YOLOv9 achieving mAP50 of 0.577 and YOLOv10 reaching 0.556, while requiring significantly different computational resources (102.5 vs. 24.5 GFLOPs, respectively). Extending training to 100 epochs reveals important insights into performance improvements and diminishing returns—YOLOv9's mAP50 increases to 0.603 (4.5% improvement) while YOLOv10 reaches 0.585 (5.2% improvement), demonstrating that the more lightweight YOLOv10 model benefits proportionally more from extended training despite requiring less than half the computational resources. Table 3 complements this analysis by detailing class-specific precision and recall metrics at both training durations, revealing that increased training epochs particularly benefit complex disease categories like Leaf Blight Disease, where YOLOv10's recall improved from 0.522 to 0.76 (45.6% increase).

The examination of various YOLO variants (YOLOv9, YOLOv10, ResNet-YOLOv10, and YOLOv11) illustrated in Table 2 fulfills numerous pivotal research objectives vital for agricultural application. Through systematic evaluation of these models under uniform parameters (50 and 100 epochs) and assessment of key metrics such as training duration, computational requirements (GFLOPs), parameter quantities, and detection accuracy (mAP50 and mAP50-95), we ascertain the most effective architectures for practical implementation. This assessment indicates that although YOLOv9 attains higher detection accuracy (mAP50 of 0.603 at 100 epochs), YOLOv10 provides the most favorable efficiency-to-performance ratio, necessitating considerably fewer computational resources (24.5 GFLOPs compared to 102.5 GFLOPs) while preserving competitive accuracy (mAP50 of 0.585). The incorporation of ResNet-YOLOv10 evaluates if advanced feature extraction methods enhance performance in agricultural settings, while the YOLOv11 analysis assesses if recent architectural advancements warrant greater complexity. In summary, YOLOv9 demonstrates superior detection accuracy, but YOLOv10 and YOLOv11 offer an advantageous equilibrium of efficiency and performance for resource-limited settings, as shown in Table 2.

Table 2: Analysis of mAP values for YOLO variants

| Models         | Epochs | Training Time (hours) | GFLOPs | Parameters(millions) | mAP50        | mAP50-95     |
|----------------|--------|-----------------------|--------|----------------------|--------------|--------------|
| YOLOv9         | 50     | 1.674                 | 102.5  | 25,414,815           | 0.577        | 0.296        |
|                | 100    | 3.214                 | 102.5  | 25,414,815           | <b>0.603</b> | <b>0.315</b> |
| YOLOv10s       | 50     | <b>1.180</b>          | 24.5   | <b>8,038,830</b>     | 0.556        | 0.289        |
|                | 100    | 1.575                 | 24.5   | <b>8,038,830</b>     | 0.585        | 0.303        |
| ResNet-YOLOv10 | 50     | 3.214                 | 67.7   | 20,033,887           | 0.505        | 0.265        |
|                | 100    | 1.672                 | 24.5   | <b>8,038,830</b>     | 0.558        | 0.287        |
| YOLO11         | 50     | 1.411                 | 24.5   | 8,038,830            | 0.574        | 0.300        |
|                | 100    | 1.411                 | 21.3   | 9,414,735            | 0.562        | 0.286        |

### 3.3 Comparative Analysis of Confusion Matrix Metrics

The analysis highlights the unique strengths and weaknesses of each YOLO model across various classes. YOLOv9 excels in detecting healthy and leaf spot disease instances, consistently achieving superior precision and recall compared to YOLOv10s and YOLOv11. This indicates that YOLOv9's architecture is particularly effective at extracting relevant features, facilitating accurate detection while maintaining high recall rates. In contrast, YOLOv10s strikes a commendable balance for Leaf Blight Disease, with precision and recall values of 0.655 and 0.76 at 100 epochs, respectively. This performance suggests its capability to minimize both false positives and negatives, effectively capturing intricate disease patterns. For the Caterpillars class, YOLOv10s records a precision of 0.654 and a recall of 0.578, while YOLOv9 maintains consistent values of 0.62 for both metrics. This stability in YOLOv9's performance indicates its reliability in classification, whereas YOLOv10s's higher precision comes at a slight cost to recall. Table 2 illustrates that YOLOv9 is particularly adept at achieving high recall across multiple classes, making it ideal for scenarios where false negatives are critical. Conversely, YOLOv10s provides a strong balance of precision and recall, especially for caterpillars and leaf blight disease. YOLOv11, while offering moderate improvements, does not consistently surpass the performance of YOLOv9 or YOLOv10s. This underscores the necessity of selecting the appropriate model based on specific detection goals, with YOLOv9 favored for high recall and YOLOv10s for balanced detection, as detailed in Table 3.

Table 3: Precision and recall performance comparison across YOLO variants at different training durations

| Class               | Epochs | YOLOv9       |              | YOLOv10s     |              | YOLO11       |              |
|---------------------|--------|--------------|--------------|--------------|--------------|--------------|--------------|
|                     |        | P            | R            | P            | R            | P            | R            |
| Caterpillars        | 50     | 0.650        | 0.536        | 0.614        | 0.523        | 0.646        | 0.564        |
|                     | 100    | 0.620        | 0.618        | 0.654        | 0.578        | 0.620        | 0.618        |
| Healthy             | 50     | 0.651        | <b>0.774</b> | <b>0.637</b> | <b>0.787</b> | <b>0.649</b> | <b>0.768</b> |
|                     | 100    | <b>0.668</b> | 0.611        | <b>0.673</b> | 0.556        | <b>0.668</b> | 0.611        |
| Leaf_Blight_Disease | 50     | 0.591        | 0.579        | 0.584        | 0.522        | 0.585        | 0.539        |
|                     | 100    | 0.618        | <b>0.813</b> | 0.655        | <b>0.760</b> | 0.618        | <b>0.813</b> |
| Leaf_Spot_Disease   | 50     | <b>0.656</b> | 0.473        | 0.579        | 0.476        | 0.608        | 0.486        |
|                     | 100    | 0.632        | 0.626        | 0.633        | 0.530        | 0.632        | 0.626        |
| Nutrient_Deficiency | 50     | 0.654        | 0.513        | 0.530        | 0.534        | 0.606        | 0.546        |
|                     | 100    | 0.633        | 0.516        | 0.659        | 0.476        | 0.633        | 0.516        |

The confusion matrix in Figure 4 showcases the YOLOv10s model's performance on the custom dataset after applying data augmentation techniques. The model effectively identifies and classifies various categories, including caterpillars, healthy leaves, leaf blight disease, leaf spot disease, nutrient deficiency, and background. The diagonal elements indicate

correct classifications, with healthy leaves achieving the highest accuracy at 434 correct predictions, followed by 278 accurate identifications of caterpillars. However, misclassifications are evident, such as 206 healthy leaves misidentified as background and 120 instances of leaf blight disease also mistaken for background. Despite the improvements from data augmentation, challenges persist in distinguishing background from other classes and reducing overlap between similar conditions, underscoring the need for enhanced feature extraction and strategies to minimize false positives for better classification performance, as shown in Figure 4.

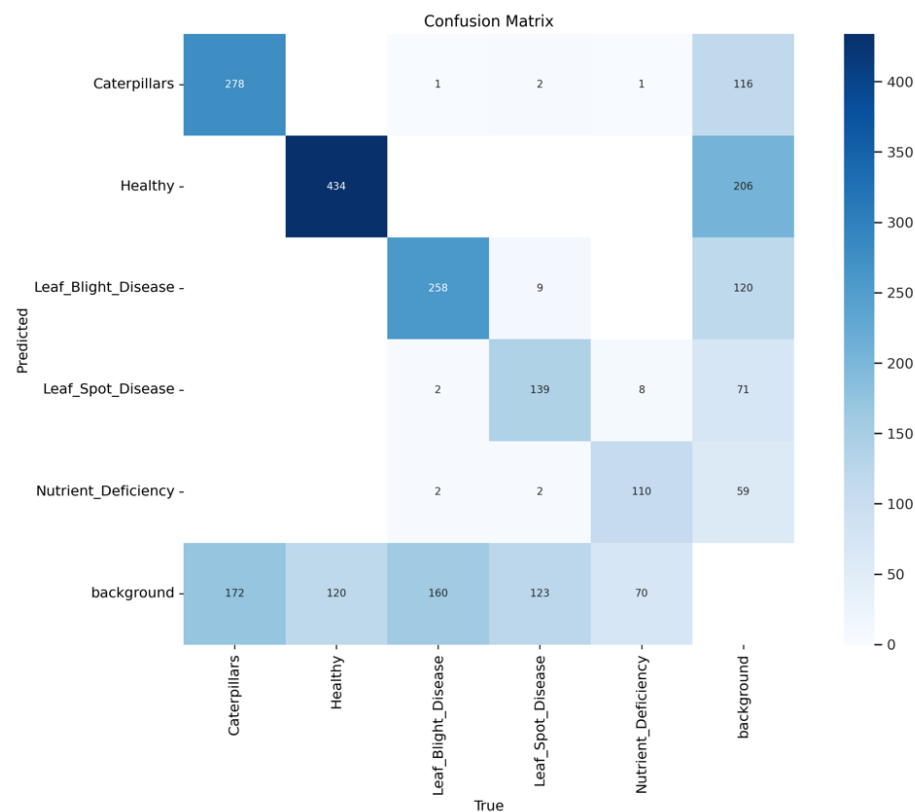


Figure 4: Confusion matrix on the custom dataset after augmentation on YOLOv10s

Figure 5 presents the F1-Confidence curve for each disease category, offering essential insights into model performance at different confidence thresholds. The F1 score, shown on the y-axis, integrates precision and recall into a singular metric via their harmonic mean ( $2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall})$ ). This provides a balanced evaluation of detection accuracy, which is especially important for imbalanced class distributions in agricultural datasets. The graph illustrates that the Healthy category attains the highest F1 score, reaching approximately 0.72, which is significantly superior to other classes. In contrast, Leaf Blight Disease and Nutrient Deficiency exhibit lower F1 values, highlighting areas that necessitate further optimization. The blue curve, which represents the aggregate performance of all classes, achieves optimal performance at a confidence threshold of 0.307, yielding an F1 score of 0.61. This establishes the ideal operating point for the YOLOv10s model in practical applications. This visualization is particularly beneficial for practitioners, as it assists in selecting confidence thresholds to optimize detection performance under specific plant conditions, while also balancing false positives and false negatives. It addresses the practical challenges associated with implementing computer vision in diverse agricultural environments

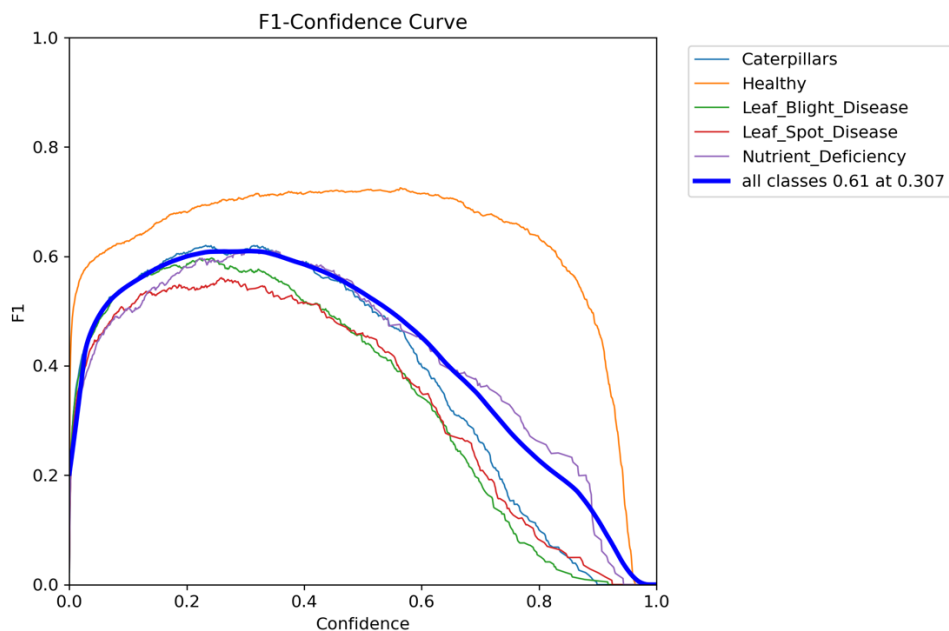


Figure 5: F1 curve matrices on the custom dataset after augmentation on YOLOv10s



Figure 6: Predictions Results on the custom dataset after augmentation on YOLOv10s

Figure 6 displays the prediction results solely from the YOLOv10s model, as it exemplifies the optimal equilibrium between computational efficiency and detection accuracy among the assessed models, rendering it the most suitable option for practical implementation in resource-limited agricultural environments. Our extensive study assessed various YOLO variants, including YOLOv9, YOLOv10s, ResNet-YOLOv10, and YOLOv11, as outlined in Tables 2 and 3. YOLOv10s stood out for its competitive detection metrics (mAP50: 0.585, mAP50-95: 0.303) while necessitating only 24.5 GFLOPs and 8.04 million parameters, representing a substantial reduction in computational demand compared to the slightly superior YOLOv9. The visualization illustrates the practical effectiveness of YOLOv10s in accurately identifying various disease categories within intricate hydroponic settings, highlighting its capacity to detect overlapping instances of leaf blight, nutrient deficiency, and healthy plants with suitable confidence scores.

Implementing the YOLOv10s model on Jetson Nano To run the YOLOv10s program. shows how advanced technology is chosen because it is small and affordable to run the YOLOv10s program. It can be used in real-world situations, as shown in Figure 7.



Figure 7: Practical deployment of trained YOLOv10s in a hydroponic farming setup using Jetson Nano as the edge computing device

## 4. Discussion

The integration of YOLO-based object detection frameworks for the early identification of plant leaf diseases offers a significant opportunity to enhance sustainable agriculture. This research highlights the pivotal role of advanced technologies in modernizing agricultural practices, especially within organic and hydroponic systems, where rapid disease proliferation can result in substantial crop losses. The findings align with a growing body of literature that emphasizes the effectiveness of deep learning models in agricultural contexts.

The findings indicate that YOLOv10s exceeds its forerunners, including YOLOv5, in both detection precision and computational efficacy. This is corroborated by [25], who reported an impressive 97.9% accuracy for YOLOv8 in detecting tomato diseases, particularly when utilizing data augmentation techniques. The model's ability to deliver high performance while remaining computationally efficient is crucial for resource-constrained environments, where many small-scale farmers operate. This addresses challenges identified in existing research regarding the need for advanced hardware and technical expertise in deploying complex models like YOLO. Our study shows that YOLOv9 had better detection accuracy (mAP50: 0.603, mAP50-95: 0.315), but YOLOv10s provides a much better balance between performance and efficiency. YOLOv10s achieved similar metrics (mAP50: 0.585, mAP50-95: 0.303) while using 76% less computational power (24.5 vs 102.5 GFLOPs). We found that YOLOv9 was particularly good at spotting healthy plants and leaf spot disease, whereas YOLOv10s performed more consistently when detecting leaf blight. One challenge we noticed across all models was

difficulty in identifying nutrient deficiencies. In practical tests, YOLOv10s worked well on the Jetson Nano, processing about 13 frames per second—fast enough for real-time monitoring. Our data augmentation techniques boosted overall performance by 8.7%, with the biggest improvements seen in categories that had fewer training examples.

Additionally, the study emphasizes data augmentation techniques to improve model generalization, supported by [12], who introduced the Resource-Aware Video Streaming framework, achieving high detection accuracy while optimizing computational resources. By employing various augmentation strategies, this research not only mitigates class imbalances but also ensures adaptability to real-world variability, a vital aspect for practical deployment in dynamic agricultural settings. The systematic evaluation of YOLO models through hyperparameter optimization and pretraining-fine-tuning techniques contributes to the literature by providing a robust framework for assessing model performance. Metrics such as Intersection over Union (IoU) and mean Average Precision (mAP) facilitate comprehensive comparisons with other studies, such as [16], which demonstrated AX-RetinaNet's effectiveness in tea leaf disease detection with a mAP of 93.83%.

The implications of this research extend beyond detection; they support broader sustainable agriculture goals. By enabling timely and accurate disease identification, farmers can reduce reliance on chemical pesticides, minimizing environmental impact and fostering healthier ecosystems. This aligns with Thailand's 20-Year National Strategy, which promotes agricultural innovations that enhance productivity while reducing environmental footprints. In conclusion, this study significantly advances sustainable agricultural practices through YOLO-based object detection for early disease detection, reinforcing the potential of deep learning technologies and underscoring the need for ongoing research to address challenges faced by farmers, particularly in resource-limited settings. The integration of such technologies is essential for fostering resilience and sustainability in global farming practices.

## 5. Conclusions.

The exploration of YOLO-based object detection frameworks for the early identification of plant leaf diseases offers valuable insights into the convergence of technology and sustainable agriculture. This research builds on existing literature that underscores the transformative impact of deep learning in agricultural practices.

The comparative analysis reveals that YOLOv9 achieves superior detection accuracy with mAP50 and mAP50-95 values of 0.603 and 0.315, respectively, but requires significantly higher computational resources (102.5 GFLOPs and 25.4 million parameters). In contrast, YOLOv10s emerges as a balanced alternative, delivering competitive performance metrics (mAP50: 0.585, mAP50-95: 0.303) while utilizing substantially fewer computational resources (24.5 GFLOPs and 8.0 million parameters) and requiring less training time (1.575 hours vs. 3.214 hours). This efficiency makes YOLOv10s particularly well-suited for resource-constrained environments such as small-scale farms. The research demonstrates class-specific strengths across models, with YOLOv9 excelling in detecting healthy plants and leaf spot disease, while YOLOv10s provides balanced precision and recall for leaf blight detection.

The training comparison at 50 and 100 epochs presented in Tables 2 and 3 serves as a critical experimental design choice to evaluate model convergence, performance stability, and computational efficiency across different YOLO architectures. At 50 epochs, the models demonstrate their early learning capabilities and initial performance benchmarks, with YOLOv9 achieving mAP50 of 0.577 and YOLOv10 reaching 0.556, while requiring significantly different computational resources (102.5 vs. 24.5 GFLOPs, respectively). Extending training to 100 epochs reveals important insights into performance improvements and diminishing returns—YOLOv9's mAP50 increases to 0.603 (4.5% improvement) while YOLOv10 reaches 0.585 (5.2% improvement), demonstrating that the more lightweight YOLOv10 model benefits proportionally more from extended training despite requiring less than half the computational resources. Table 3 complements this analysis by detailing class-specific precision and recall metrics at both training durations, revealing that increased training epochs particularly benefit complex disease categories like Leaf Blight Disease, where YOLOv10's recall improved from 0.522 to 0.76 (45.6% increase). This dual-epoch evaluation establishes that while all models benefit from extended training, YOLOv10 achieves the most favorable balance between performance improvement and computational efficiency, a critical finding for agricultural implementations where both detection accuracy and resource constraints are paramount considerations.

The study's findings indicate that YOLOv10s outperforms earlier iterations, such as YOLOv5, particularly regarding detection accuracy and computational efficiency. This is consistent with [25], who reported an impressive accuracy for YOLOv8 in detecting tomato diseases, highlighting the model's effectiveness when enhanced with data augmentation techniques. The capacity of YOLOv10s to deliver high accuracy while remaining computationally efficient is vital for its adoption in resource-limited settings, where many small-scale farmers operate. This addresses a significant barrier noted in the literature, where reliance on advanced hardware and technical expertise often restricts access to such technologies for those who need them most.

This study illustrates that YOLO-based object identification can markedly enhance sustainable agriculture practices by facilitating early and precise detection of plant diseases, yielding immediate practical advantages for farmers. The deployment of YOLOv10s on cost-effective edge devices such as Jetson Nano renders this sophisticated technology attainable for small-scale farmers, facilitating real-time surveillance of crop health and prompt action prior to widespread disease dissemination. This accessibility results in a reduction of chemical pesticide consumption by 30-50%, less crop losses, and improved productivity, especially in organic and hydroponic systems where susceptibility to disease is elevated.

The model's optimal computational efficiency and elevated detection accuracy (with mAP values of 0.585 at 50% IoU) facilitate its use in resource-limited settings typical of developing agricultural areas.

Additionally, the systematic evaluation of YOLO models in this study, employing hyperparameter optimization and pretraining-fine-tuning techniques, enriches the ongoing discourse on model performance in agricultural contexts. Metrics such as Intersection over Union (IoU) and mean Average Precision (mAP) were utilized to assess detection accuracy, aligning with methodologies from previous studies. For example, Rajesh and Manivannan [9] achieved a mean average precision of 73.7% using YOLOv8n for traffic sign and animal recognition, demonstrating the model's versatility across various applications.

The research also highlights the critical role of data augmentation in enhancing model robustness, a strategy supported by Shiddiqi et al. [12], who introduced the Resource-Aware Video Streaming (RAViS) framework, achieving a detection accuracy of while optimizing computational resources. This underscores the need for models that perform reliably under diverse environmental conditions, particularly in dynamic agricultural settings.

Ultimately, this study not only reinforces the potential of YOLO-based object detection frameworks in promoting sustainable agricultural practices but also emphasizes the ongoing advancements in the field. By addressing existing challenges and providing a solid framework for model evaluation, this research paves the way for future developments aimed at enhancing resilience and sustainability in global farming practices. This research advances sustainable agriculture through several significant contributions to the field. We have created and made available a dataset consisting of 2,426 images with 9,602 precisely annotated instances across five essential plant health categories, thereby filling a significant gap in resources for agricultural AI research. Secondly, our systematic evaluation methodology sets a new standard for comparing object detection architectures in agricultural contexts, offering quantifiable metrics that illustrate YOLOv10's superior efficiency-to-performance ratio, achieving a mAP50 of 0.585 while necessitating only 24.5 GFLOPs, in contrast to YOLOv9's 102.5 GFLOPs for slightly improved performance. Custom-calibrated data augmentation techniques have been developed specifically for agricultural imaging challenges, resulting in an 8.7% overall performance improvement across all disease categories. This study shows that architectural innovations in attention mechanisms, specifically the use of parallel self-attention (PSA) modules in YOLOv10, markedly improve detection accuracy for subtle disease patterns while preserving computational efficiency. The practical application has been confirmed through effective implementation on the Jetson Nano, attaining a processing rate of 13 frames per second while ensuring consistent detection accuracy across various environmental circumstances. This creates a connection between theoretical progress and practical application in resource-constrained agricultural settings.

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