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Detection of Disease in Platycerium Ornamental Plant Leaves Using Yolo 12

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ABSTRACT

Platycerium is an epiphytic ornamental plant with high aesthetic and economic value, thus requiring proper care. Identifying Platycerium leaf diseases based on visual symptoms often requires precision and experience, thus necessitating an image-based automated approach. This study aims to develop a Platycerium leaf disease detection model using the deep learning-based YOLO method. The model was developed using Kaggle Notebook with P100 GPU support. The dataset used consisted of three disease classes, namely Bacterial Leaf Spot, Fern Scale, and Rizoctonia Blight. Model training was carried out with variations in the number of epochs of 50, 75, and 100 epochs, and evaluated using the Precision, Recall, and Mean Average Precision (mAP) metrics. The results showed that training with 50 epochs gave the best results with a mAP50 value of 0.953 and mAP50–95 of 0.577. Testing using test data and data outside the dataset showed that the model was able to detect Platycerium leaf disease in test images by displaying bounding boxes and class labels. Based on these results, the YOLO model developed can be used as an image-based approach for detecting Platycerium leaf disease and can be further developed.

1. Introduction

Ornamental plants serve primarily as decorative elements to add natural beauty and aesthetic value to home and corporate environments (Yaman, 2023). In recent years, the cultivation of ornamental plants has expanded rapidly in Indonesia, driven by an increasing public awareness of environmental conservation and landscape aesthetics (Mareta Tama & Candra Noor Santi, 2023). Among various popular plant groups, the genus Platycerium has stood out due to its highly unique, broad leaf shapes resembling deer antlers, earning it the common moniker 'simbar' (Pertama et al., 2023).

Platycerium is an epiphytic genus comprising approximately 15 to 18 species that are cultivated and traded in horticultural markets worldwide (Camloh & Ambrožič-Dolinšek, 2010). Based on field interviews with Ni Luh Putu Andriani, a prominent Platycerium nursery owner in Gianyar Regency, consumer demand for this unique plant surged during the COVID-19 pandemic as a therapeutic and decorative hobby. This phenomenon aligns with market analysis reports in Trubus.id by Erliana (2024), titled "Tren Tanaman Hias 2024: Pasar Platycerium Terbuka Lebar," which highlights a massive increase in demand. Maulana Yusuf, owner of Ciapus Nursery in West Java, reported that his Platycerium sales rose by 50-60% in 2023 compared to 2022. Around 80% of these buyers originate from Bali, with the remaining market distributed across Jakarta, West Java, and Banten.

Despite its high economic and aesthetic value, cultivating Platycerium presents severe challenges. The plants are highly susceptible to various pathogenic leaf diseases which degrade their physical health, aesthetic value, and subsequent economic price (Darryil Ruprecht, 2021). Identifying these diseases based solely on visual inspections of leaf surfaces is difficult, particularly for novice growers and hobbyists. According to nursery operators Ni Luh Putu Andriani and Putu Angga Putra Gunawan, current diagnostic practices depend heavily on consulting expert horticulturists or experienced hobbyists via message threads, which is often slow and prone to errors. Delayed or incorrect diagnosis worsens plant conditions, leading to irreversible damage and high financial losses.

Observations conducted at three commercial nurseries in Bali (Kebun Platycerium in Ubud, Living Plant in Mengwi, and Platy Djoemah in Sukawati) identified three major leaf diseases that regularly afflict Platycerium: Fern Scale (Pinnaspis aspidistrae), Rhizoctonia Blight (Rhizoctonia solani), and Bacterial Leaf Spot (Pseudomonas cichorii). Developing an automated visual diagnostic tool is crucial to enable timely intervention.

The application of computer vision and deep learning in agriculture has demonstrated immense potential for plant disease classification and detection (Upadhyay et al., 2025). In object detection tasks, the You Only Look Once (YOLO) framework is widely favored for its outstanding performance in executing real-time detection with exceptional speed and high precision (Rajasekhar, 2024). Numerous studies have successfully used YOLO to diagnose crop anomalies. For instance, Bitra and Dewi (2024) developed a YOLOv8-based model to detect coffee leaf diseases (miner, rust, phoma, and healthy), obtaining a mean Average Precision (mAP) of 97.8%, precision of 95.2%, and recall of 96.6%. Riva and Jayanta (2023) utilized YOLOv5 with varied split-data ratios to detect chili plant diseases (leaf spot, leaf blight, anthracnose, and whitefly), achieving a precision of 94.6% and mAP@0.5 of 95.9%. Additionally, Ardiansyah and Hasan (2023) implemented YOLOv7 for coffee leaf disease categorization, reporting an F1-score of 0.93. Manurung et al. (2024) employed YOLOv8 to identify potato beetles and larvae with a mAP50 of 82.5%, while Firgia and Thomas (2023) introduced YOLOv5s with Spatial Pyramid Pooling (SPP) for corn disease detection, yielding a mAP of 0.795.

While deep learning algorithms have been heavily applied to agricultural staple crops, no literature has addressed automated disease detection specifically for Platycerium ornamental plants. This study addresses this research gap by building a robust, automated detection model leveraging the newly released YOLOv12 model. YOLOv12 represents a significant milestone in computer vision, offering superior multi-scale feature extraction, increased accuracy on tiny bounding boxes, and optimized latency compared to prior versions. The findings of this research will establish a foundational framework for automatic visual diagnostics in ornamental horticulture and guide mobile-based application developers.

2. Literatur Review

To provide a strong academic context, this section defines the biological nature of target Platycerium diseases and outlines the architectural foundations of YOLOv12 and Convolutional Neural Networks.

Fern Scale (Pinnaspis aspidistrae): Fern Scale is a highly destructive insect pest that colonizes Platycerium leaf lobes. The scale insects suck essential plant sap directly from the foliage, leading to localized leaf wilting, structural distortion, and progressive chlorosis (yellowing). Severely infested young plants suffer rapid death if left untreated (Darryil Ruprecht, 2021).

Rhizoctonia Blight (Rhizoctonia solani): A fungal disease that manifests as irregular, brown-to-black necrotic lesions on Platycerium fronds, especially on base shield leaves. It proliferates rapidly in warm, humid microclimates, which are typically exacerbated by excessive watering. If untreated, it spreads to vegetative growth points, killing the host plant (Darryil Ruprecht, 2021).

Bacterial Leaf Spot (Pseudomonas cichorii): This bacterial pathogen causes small, dark, water-soaked brown lesions with a distinct yellow halo. The spots enlarge rapidly under favorable conditions, sometimes expanding past 2.5 cm and coalescing to destroy the visual and physical integrity of the leaf (Darryil Ruprecht, 2021).

Deep Learning and Convolutional Neural Networks (CNN): Deep learning (DL) mimics the human brain's neural networks to capture intricate abstractions from unstructured data, such as images (Sharifani & Amini, 2023). CNNs are the gold standard for image processing, utilizing convolutional layers to apply kernel filters and extract spatial feature maps, pooling layers (such as max and average pooling) to reduce dimension and combat overfitting, and fully connected layers to map high-level features into final classification predictions (Jain et al., 2024; Zafar et al., 2024).

YOLO 12 and Roboflow: The YOLO framework revolutionized object detection by introducing a single-stage neural network that predicts bounding box coordinates and class confidence scores directly from a single forward pass (Rajasekhar, 2024). This study adopts YOLOv12, which implements improved attention mechanisms and feature aggregation to detect complex symptoms. Roboflow serves as the cloud preprocessing workspace, facilitating image annotation, random data augmentation, image normalization, and multi-format dataset partitioning (Saepudin et al., 2024).

3. Research Method

Data Gathering Techniques

To gather a robust research dataset, two primary techniques were employed. Primary data collection involved on-site optical photography of diseased Platycerium leaves using high-resolution mobile cameras under varying natural lighting conditions. Additionally, structured interviews were held with expert Platycerium breeders Ni Luh Putu Andriani and Putu Angga Putra Gunawan. Secondary data collection was executed by synthesizing textbook concepts and academic journals covering CNN structures, YOLO revisions, and agricultural vision systems.

Fern Scale *Rhizoctonia Blight* *Bacterial Leaf Spot*

Fig 1. Sample of the Platycerium disease dataset

Automated Diagnostic Flow

The automated diagnostic pipeline takes an optical RGB image of a Platycerium leaf as input. The image is evaluated through the trained YOLOv12s model. If specific patterns corresponding to the three target classes (Fern Scale, Rhizoctonia Blight, and Bacterial Leaf Spot) are identified, the system outputs the leaf image rendered with bounding box coordinates, class labels, and corresponding probability confidence scores. If the leaf is healthy or symptoms do not exceed the confidence threshold, no bounding boxes are drawn.

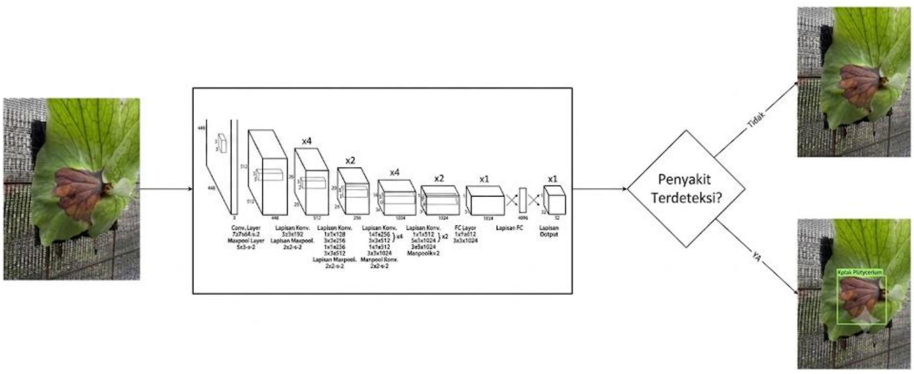

Fig 2. Automated Diagnostic flow

Systematic Research Stages

The study is systematically divided into nine consecutive phases: (1) Literature review to design model parameters; (2) Site planning and coordination; (3) Image dataset collection; (4) Preprocessing, including bounding box drawing and labeling on Roboflow; (5) Split partitioning (70% train, 20% validation, 10% test); (6) Augmentation to enrich visual variety; (7) Environment compilation on Kaggle Notebook with Ultralytics; (8) Model training with 50, 75, and 100 epoch variations; and (9) Performance comparison and model testing using unseen test images and out-of-dataset pictures.

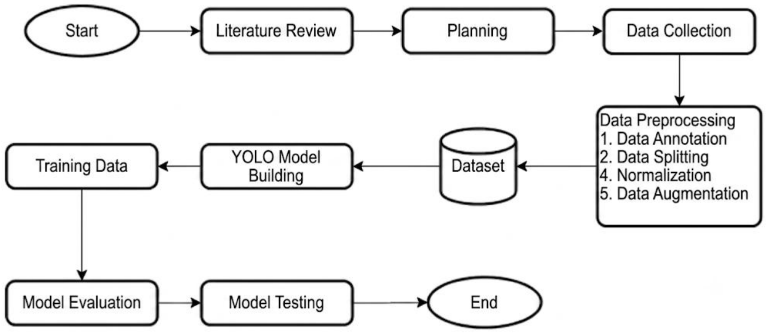

Fig 3. Systematic Research Stages

Pre-processing and Augmentation Parameters

Image normalization involved scaling all collected leaf images to a standard dimension of stretch 640x640 pixels to ensure network uniform input. To expand the dataset size and enhance model generalization in outdoor settings, five augmentation techniques were applied: horizontal and vertical flips; random rotations within ±15°; shear transformations up to 10° vertically and horizontally; exposure adjustment of 10% to mimic sun glares; and a 1-pixel Gaussian blur to simulate camera defocus.

Evaluation Mathematics

The model's visual diagnostic performance is measured using four widely standard evaluation metrics: Precision, Recall, F1-Score, and Mean Average Precision (mAP). Precision measures the exactness of positive predictions, Recall calculates the model's sensitivity in capturing positive cases, and F1-Score acts as the harmonic mean balancing both measures. The formulas are constructed as follows:

$$Precision = TP / (TP + FP) \quad (1)$$

$$Recall = TP / (TP + FN) \quad (2)$$

$$F1\text{-}Score = 2 * (Precision * Recall) / (Precision + Recall) \quad (3)$$

$$mAP = (1 / N) * sum(AP\_i) \quad (4)$$

Where TP, FP, and FN correspond to True Positives, False Positives, and False Negatives, respectively, and N denotes the total number of disease classes (N = 3).

4. Result and Discussions

Original and Augmented Dataset Structure

Primary fieldwork resulted in 1,200 raw high-quality Platycerium leaf images, which were partitioned evenly with 400 images for Bacterial Leaf Spot, 400 images for Rhizoctonia Blight, and 400 images for Fern Scale. Post-annotation on Roboflow, the raw dataset was divided randomly into 845 images for training (70%), 235 images for validation (20%), and 120 images for testing (10%). By applying the multi-technique augmentations with a maximum version limit of 3x, the training partition was successfully expanded, yielding an augmented dataset of **2,890 images** ready for deep learning training.

Table 2. YOLOv12s Training Metrics across Epoch Scenarios

Sceanrio	Disease Class	Precision	Recall	mAP50	mAP50-95
50 Epochs	Bacterial Leaf Spot	0.857	0.844	0.908	0.458
50 Epochs	Fern Scale	0.929	0.931	0.976	0.552
50 Epochs	Rhizoctonia Blight	0.946	0.944	0.975	0.719
50 Epochs (Avg)	**All Classes**	**0.911**	**0.906**	**0.953**	**0.577**
75 Epochs	Bacterial Leaf Spot	0.853	0.867	0.902	0.456
75 Epochs	Fern Scale	0.931	0.920	0.971	0.554
75 Epochs	Rhizoctonia Blight	0.942	0.944	0.979	0.719
75 Epochs (Avg)	**All Classes**	**0.909**	**0.910**	**0.951**	**0.576**
100 Epochs	Bacterial Leaf Spot	0.880	0.818	0.897	0.448
100 Epochs	Fern Scale	0.955	0.894	0.976	0.551
100 Epochs	Rhizoctonia Blight	0.937	0.901	0.971	0.713
100 Epochs (Avg)	**All Classes**	**0.924**	**0.871**	**0.948**	**0.571**

Performance Analysis of Sscenario Variations

An analysis of Table 2 reveals that training the YOLOv12s model for 50 epochs achieved the absolute highest detection performance, with a mean Average Precision at standard threshold (mAP50) of **0.953** and a strict mAP50-95 of **0.577**. Under this 50-epoch scenario, Rhizoctonia Blight was detected with outstanding precision (0.946) and recall (0.944), followed by Fern Scale (precision 0.929, recall 0.931), and Bacterial Leaf Spot (precision 0.857, recall 0.844).

Interestingly, extending the training duration to 75 and 100 epochs did not yield any performance improvements, but instead led to a minor decrease in evaluation metrics. At 75 epochs, mAP50 fell slightly to 0.951, and at 100 epochs, it settled at 0.948. This trend is a typical indicator of overfitting: as epochs increase beyond 50, the model begins memorizing localized training noise and background artifacts rather than generalized biological symptoms, reducing its validation precision. Therefore, the 50-epoch model was selected as the optimal candidate for final diagnostic testing.

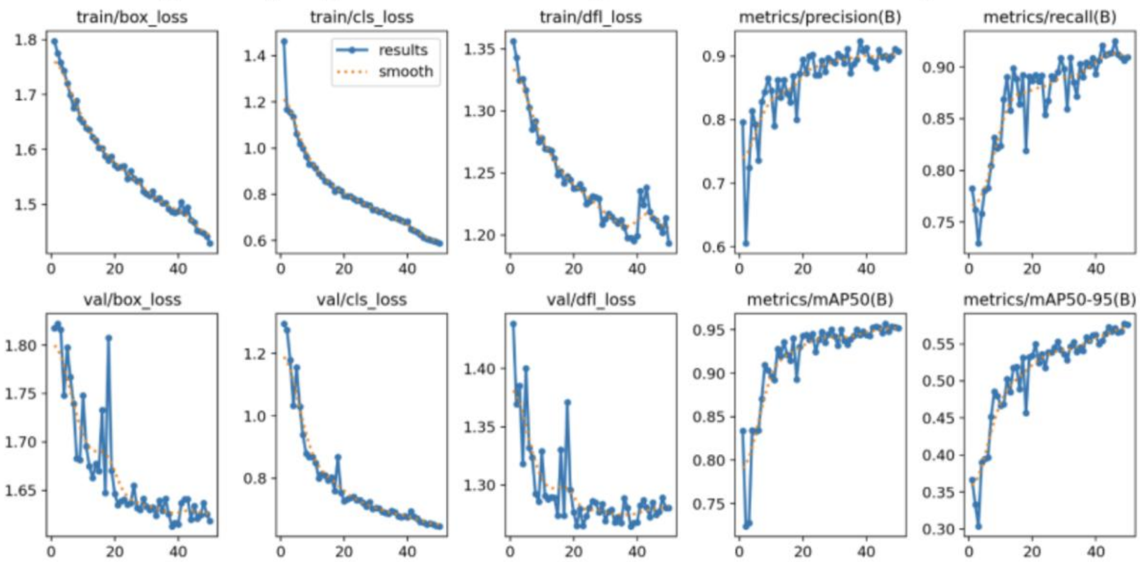

Fig 3. Performance Analysis of Scenario Variations

Confusion Matrix Evaluation

To closely evaluate misclassifications at 50 epochs, the resulting confusion matrix values were examined. For Bacterial Leaf Spot, 1,258 instances were correctly predicted as True Positives (TP); however, 276 background or alternative symptoms were falsely flagged as spot disease (FP), and 110 leaf spot instances were missed (FN). For Fern Scale, the model recorded an exceptional 1,502 True Positives, with 190 False Positives and 45 False Negatives. For Rhizoctonia Blight, 67 True Positives were recorded, with only 5 False Positives and 4 False Negatives, demonstrating superb class discrimination despite its smaller overall area representation in bounding box counts.

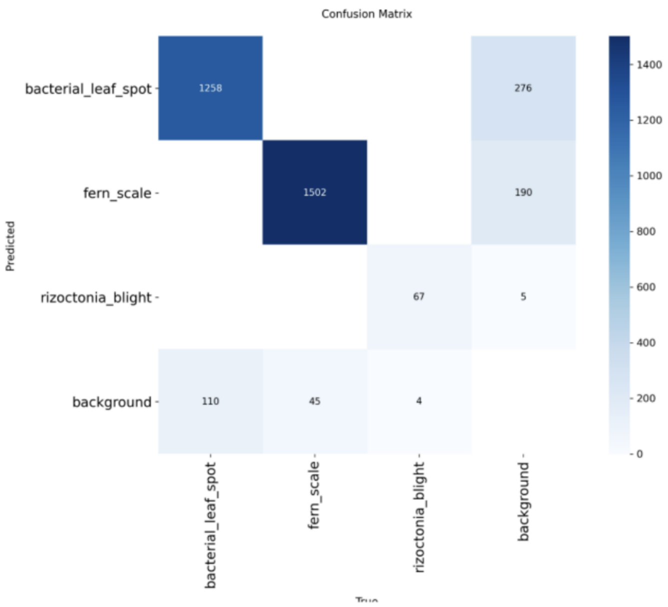

Fig 4. Performance Analysis of Sscenario Variations

Robust Generalization on Test Sets and Field Data

To test the practical viability of the optimal 50-epoch model, evaluation was performed on two test sets. First, testing on the 10% test set partitioned from the original dataset showed that the model successfully delineated leaf symptoms with highly precise bounding boxes and class labels. Second, to evaluate field robustness, the model was tested on independent Platycerium leaf images collected from nurseries outside the original dataset under varied shadows, angles, and distances. The model demonstrated excellent generalization, reliably detecting and labeling target diseases even in unstructured environments with complex background foliage, proving its suitability for commercial smartphone deployment. These robust field validation results directly resolve the core research problem; by delivering an accurate, real-time automated diagnostic tool, the system successfully eliminates the slow and error-prone reliance on expert consultations. Consequently, the research objective has been fully achieved, providing cultivators with an accessible method to execute immediate interventions and prevent irreversible plant damage and financial losses.

5. Conclusion

This research successfully built an image-based automated disease detection model for Platycerium ornamental plants using YOLOv12s, directly addressing the critical challenge of manual and error-prone visual diagnosis faced by cultivators and hobbyists. The model was evaluated against three common diseases: Fern Scale, Rhizoctonia Blight, and Bacterial Leaf Spot. Among the training variations, the 50-epoch scenario proved to be the most optimal, achieving a peak mAP50 of 0.953 and a mAP50-95 of 0.577 on validation data, whereas longer training durations caused minor overfitting. Testing on both partitioned test sets and out-of-dataset pictures confirmed robust generalization, showing that the model can accurately identify and localize visual symptoms of leaf diseases under real horticultural conditions. By providing rapid and precise automated detection, this research achieves its primary objective of eliminating the heavy reliance on time-consuming expert consultations, thereby enabling timely interventions to prevent irreversible plant damage and financial losses. For future research, five key suggestions are proposed to improve system performance: (1) Expand the dataset size and integrate additional Platycerium species and diseases; (2) Investigate alternate YOLOv12 variants (e.g., YOLOv12m or YOLOv12x) and perform grid-search hyperparameter tuning; (3) Implement a Region of Interest (ROI) preprocessing step to isolate leaves from complex nursery backgrounds; (4) Package the optimized YOLOv12 weights into lightweight mobile and web applications to assist growers in the field; (5) Integrate classification accuracy as an additional performance metric to provide a more comprehensive, multi-dimensional evaluation.

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