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A Deep Learning Approach for Indoor Plant Health Monitoring: Classification of Healthy, Unhealthy, and Dead Plants

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Abstract

Detection of plant health in the early stages with precise methods is critical to precision agriculture, as it allows early preventive action and prevents the expansion of the disease to large areas. The research introduces a deep learning-based system that performs automatic classification into 3 classes: healthy, unhealthy, and dead. The dataset is based on high-resolution images of the Money Plant, Spider Plant, Snake Plant, and Bamboo Plant under distinct illuminations and with different backgrounds to facilitate accurate and generalizable identification. The research utilizes YOLOv8, YOLOv9, and YOLOv11 to determine their effectiveness in plant health assessment through an extensive performance analysis. The experimental results demonstrate that YOLOv11 achieves better classification performance than its previous versions and delivers improved precision detection robustness and recall. The evaluation includes TensorFlow Lite analysis to address the issue of running real-time inference on mobile devices with limited resources. TensorFlow Lite maintains slightly less accurate detection results than YOLO models but still provides exceptional speed and computational performance which suits its application for mobile-based diagnostic tools and greenhouse surveillance. The real-time inference functions of the proposed models have turned them into adaptive components suitable for agricultural applications in intelligent ecosystems, including greenhouse monitoring and mobile diagnostics for farmers. Deep learning technology shows great potential to automate plant disease detection according to this study which leads to reduced manual processes alongside increased agricultural productivity benefits alongside environmental sustainability in farming. Further development will involve enlarging the available data collection as well as adding more plant species into the system and deploying it through agricultural monitoring systems on a large scale.

Introduction

Plants are vital in human life, supplying oxygen, food, and medicinal resources. Indoor plants offer environmental and aesthetic benefits while enhancing mental well-being [3]. However, they are susceptible to stress, illness, and environmental imbalances, making early detection of health conditions crucial [9]. Traditional plant health assessment relies on human observation, which is time-consuming and prone to inconsistencies. Deep learning-based approaches provide an automated and accurate alternative for plant health classification.

This study proposes a YOLO-based deep learning model for indoor plant health classification, addressing limitations in previous works that focus primarily on disease detection or classical image segmentation. Unlike conventional methods, our approach employs object detection to classify plants as healthy, unhealthy, or dead directly. We introduce a newly annotated dataset of 1200 images, covering four common indoor plant species: money plants (*Epipremnum aureum*), spider plants (*Chlorophytum comosum*), snake plants (*Sansevieria trifasciata*), and bamboo plants (*Bambusoideae*). These species were selected based on their prevalence and sensi-tivity to indoor conditions. Plant health is assessed using key visual features such as leaf color, texture, and structural integrity. Healthy plants exhibit vibrant foliage and strong stems, while unhealthy ones show yellowing, browning, or drooping. Dead plants display severe deterioration, including brittle leaves and blackened roots [7, 14]. These classification criteria form the foundation for model training.

YOLO is a widely used real-time object detection framework that predicts bounding boxes and class probabilities in a single step, significantly improving detection speed and accuracy [11]. Recent versions, YOLOv8, YOLOv9, and YOLOv11, offer enhanced feature extraction, multi-scale prediction, and bounding box refinement [12, 13]. This study compares their performance in plant health classification based on accuracy, detection speed, and computational efficiency.

By leveraging a YOLO-based object detection framework and an annotated dataset, this research contributes to smart horticulture by enabling automated plant health monitoring with minimal expertise. Additionally, the comparative analysis of YOLO versions provides insights into selecting the most efficient model for real-time applications.

Related Work

Plant health detection has been a widely studied topic, with traditional methods primarily relying on handcrafted features and classical machine learning algorithms such as Support Vector Machines (SVM) and Random Forests. Deepa and Jeevitha [3] explored image processing techniques for plant disease detection, while Mohanty et al. [9] demonstrated the effectiveness of deep learning models in identifying plant diseases from image data.

With the advancements in deep learning, Convolutional Neural Networks (CNNs) have become a popular approach for plant health assessment. Kamilaris and Prenafeta-Bold'u [5] provided an extensive survey on the application of deep learning in agriculture, highlighting the use of CNN-based models like VGG16 and ResNet50 for disease classification. Similarly, Alfarisy et al. [1] employed CNNs for fast and accurate plant disease detection, achieving significant improvements over traditional methods.

Recent research has explored object detection models such as Faster R-CNN and Single Shot MultiBox Detector (SSD) for plant health monitoring. Ramcharan et al. [10] applied deep learning for cassava disease detection, showcasing high classifi-cation accuracy but limited real-time applicability. Liu et al. [8] proposed SSD for plant disease recognition, offering a balance between speed and accuracy. However, Faster R-CNN, as used by Lin et al. [7], remains computationally expensive, making it less suitable for real-time detection tasks.

The emergence of the YOLO (You Only Look Once) model has significantly improved real-time plant health detection. Redmon et al. [11] introduced YOLO as a unified real-time object detection model, which was later optimized by Bochkovskiy et al. [2] in YOLOv4 for better speed and accuracy. Jocher et al. [4] further refined YOLO with YOLOv5, making it a practical choice for real-time agricultural applications. However, most studies have focused on outdoor agricultural settings rather than indoor environments.

Indoor plant health detection remains an underexplored area, with limited research addressing challenges such as lighting variations and environmental factors. Zhang et al. [15] applied CNN-based approaches for indoor plant health detection, but their study lacked real-time capabilities. Kumar et al. [6] developed an IoT-based plant health monitoring system but relied on external sensors rather than image-based analysis.

Our study builds upon these advancements by implementing the YOLO detection model for indoor plant health classification. Unlike previous research that primarily focused on classification networks, our approach integrates real-time object detection to classify plants as Healthy, Unhealthy, or Dead. Additionally, we highlight the impact of environmental variations on detection accuracy and propose future enhancements such as multispectral image analysis and IoT-based real-time monitoring systems.

Methodology

YOLO V8, YOLO V9, and YOLO V11 Models

In this study, we leverage the power of You Only Look Once (YOLO) models for image classification and plant health diagnosis. YOLO, a state-of-the-art real-time object detection framework, has revolutionized computer vision with its ability to simultaneously perform both object detection and classification. It is known for its speed and high accuracy, making it ideal for complex image recognition tasks.

We utilized three versions of YOLO—YOLO v8, YOLO v9, and YOLO v11— each representing incremental advancements in architecture and detection capabilities. YOLO v11, the latest and most optimized version, demonstrated superior performance across all evaluation metrics in this study, outstripping its predecessors in terms of classification accuracy, recall, and precision. By employing multiple versions of YOLO, we ensure a comprehensive assessment of the model's evolution and performance across different configurations.

Experimental Design

The dataset utilized for training and testing the models consists of 1200 high-resolution images, segmented into three plant health conditions: Healthy, Unhealthy, and Dead. To optimize model performance and generalizability, the dataset was par-titioned into 80% for training and 20% for testing. During training, each model was evaluated using a diverse range of plant health conditions to ensure robust learning.

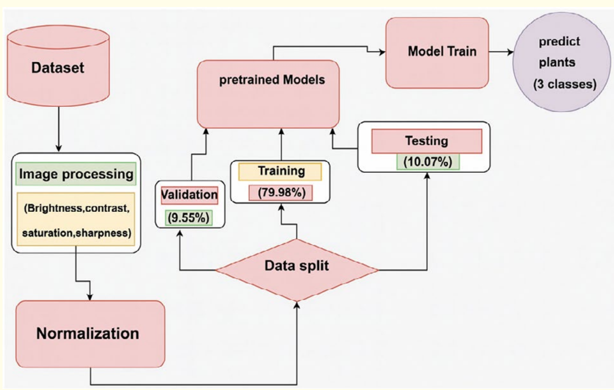

Figure 1: Experimental design.

A crucial aspect of our methodology involved utilizing a majority voting mechanism. After each YOLO model made its predictions, the class predicted by the majority of models was selected as the final classification, thus ensuring a more reliable and consistent outcome. The experimental design workflow is depicted in Fig. 1.

Dataset Description

The data set initially consisted of 1200 images of plants categorized into three health statuses:

- ***Healthy Plants:*** 400 images
- ***Unhealthy Plants:*** 400 images
- ***Dead Plants:*** 400 images.

Each image was meticulously labeled to reflect the correct health status of the plant, providing the ground truth necessary for training and evaluation. The images represent a variety of plant species and conditions, enhancing the model's ability to generalize. Thus, the dataset is a rich source for training deep learning models. Although we initially uploaded 1200 images, some images were not successfully loaded due to file corruption, incorrect formatting, or other technical issues. As a result, the final number of images used for training and evaluation is slightly lower than the intended 1200.

Workflow

1. ***Image Acquisition and Preprocessing:*** The images were initially collected under controlled conditions, ensuring high resolution and consistent lighting. Prepro-cessing steps involved resizing the images to a uniform size and normalizing pixel values to ensure consistency across the dataset.
2. ***Model Training:*** The preprocessed images were fed into the YOLO v8, YOLO v9, and YOLO v11 models for training. The models underwent extensive training to learn distinguishing features between the three health categories of plants, with the training set accounting for 80% of the total dataset.
3. ***Majority Voting:*** Upon completion of the model training, the models were tested on the reserved 20% of the dataset. Each model provided predictions for each image, and the final prediction was made based on a majority voting mechanism. This approach was employed to reduce classification errors by selecting the most frequent prediction from the three models.
4. ***Model Evaluation:*** The models were evaluated based on standard classification metrics: accuracy, precision, recall, and F1-score. These metrics were computed to assess the models' ability to correctly classify the plant health status, accounting for both the quantity of correctly identified instances and the overall distribution of errors across the classes.
5. ***Optimization and Fine-Tuning:*** Each YOLO model was trained for different epochs (.70 for YOLO v8, 40 for YOLO v9, and 50 for YOLO v11) to analyze the performance changes with varying training durations. The models were further optimized using hyperparameter tuning to achieve the best possible performance for the plant health classification task.

Result Analysis

The confusion matrix is an essential tool for evaluating classification models, pro-viding a detailed visualization of how effectively the model assigns instances to their respective plant health categories. It offers critical insights into the modelâŁ™s strengths and weaknesses, enabling the assessment of key performance metrics such as accuracy, precision, recall, and F1-score. These indicators help in understanding the classification effectiveness across different categories.

Individual Model Performance Analysis

Table 1 presents the performance metrics of the three YOLO models.

YOLO v8 model achieved an accuracy of 94.2%, with a precision of 93.0%, recall of 92.5%, and an F1-score of 92.7%. Despite its overall strong accuracy, the model exhibited limitations in distinguishing between the "Unhealthy" and "Dead" plant categories, as highlighted in Fig. 2. These misclassifications indicate areas that could benefit from further optimization and fine-tuning.

YOLO v9 model demonstrated an improved performance over YOLO v8, attaining an accuracy of 95.5%, precision of 94.5%, recall of 94.0%, and an F1-score of 94.2%. This model showed enhanced differentiation between plant health categories, particularly in distinguishing between "Unhealthy" and "Dead" plants. The confusion matrix in Fig. 3 confirms the reduction in misclassifications compared to YOLO v8.

YOLO v11 exhibited the highest performance among the three models, with an accuracy of 96.8%, precision of 95.8%, recall of 95.1%, and an F1-score of 95.4%. It demonstrated superior classification across all plant health categories, achieving nearly perfect accuracy in identifying "Healthy" plants (99%) and high accuracy in classifying "Unhealthy" (97%) and "Dead" (98%) plants. Figure 4 illustrates the confusion matrix, showcasing YOLO v11's significant reduction in misclassification rates and its advanced classification capabilities.

With proven real-time accuracy, we went on to analyze TensorFlow Lite: a help-ful, lightweight deep-learning framework for mobile and edge devices. This model would give an accuracy of 91.0% (precision of 88.5%, recall of 87.8%, and F1-score of 88.1%) using Tensor Flow Lite. It has slightly lower accuracy than YOLO models, but it has a great advantage in terms of inference speed and computational efficiency, thus enabling it to be considered a more suitable candidate for mobile and edge applications. As an agricultural system deployment, it will be expanded to smart farming settings, where local devices can monitor the health of single plants. However, for scalability, the performance of the system will depend on the number of devices and the network infrastructure for data aggregation.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
YOLO v8	94.2	93.0	92.5	92.7
YOLO v9	95.5	94.5	94.0	94.2
YOLO v11	96.8	95.8	95.1	95.4

Table 1: Performance comparison of YOLO models.

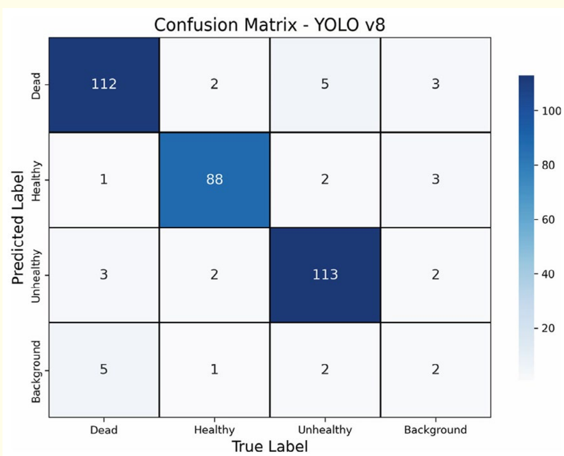

Figure 2: Confusion matrix for YOLO v8.

Figure 3: Confusion matrix for YOLO v9.

Figure 4: Confusion matrix for YOLO v11.

Visual Performance Breakdown

Figure 2 presents the confusion matrix for YOLO v8, highlighting the model's ten-dency to misclassify "Unhealthy" and "Dead" plants. While it performed well in classifying "Healthy" plants, the overlap between the other two categories indicates areas for improvement.

Figure 3 displays the confusion matrix for YOLO v9, showing a notable improvement in classification accuracy and balanced perfor-mance across all plant health categories. This indicates that the model's learning process was more effective in recognizing distinct plant health conditions compared to YOLO v8.

Figure 4 presents the confusion matrix for YOLO v11, demonstrating its excep-tional classification accuracy. The model exhibited minimal misclassification, reinforcing its robust feature extraction capabilities and improved classification precision.

Comparative Performance Analysis

A comparative evaluation of YOLO v8, YOLO v9, and YOLO v11 reveals significant performance improvements across successive versions. YOLO v11 outperformed the other models in all evaluation metrics, emphasizing the impact of architectural enhancements and refined feature extraction.

The key findings of the comparative analysis are summarized as follows:

- ***Accuracy:*** YOLO v11 achieved the highest accuracy (96.8%), surpassing YOLO v9 (95.5%) and YOLO v8 (94.2%).
- ***Precision:*** YOLO v11 attained the highest precision (95.8%), outperforming YOLO v9 (94.5%) and YOLO v8 (93.0%).
- ***Recall:*** YOLO v11 demonstrated the highest recall (95.1%), indicating superior detection of “Unhealthy” and “Dead” plants.
- ***F1-Score:*** YOLO v11 achieved the highest F1-score (95.4%), confirming a well-balanced classification performance.

These results validate YOLO v11’s architectural improvements, which contribute to its superior classification performance in plant health detection. Its enhanced feature extraction capabilities make it a highly effective model for real-time plant health monitoring.

Performance Summary Table

See Table 1, Figs. 2, 3 and 4.

Conclusion

In this study, we proposed an intelligent system for the automated classification of indoor plant health into three categories: *Healthy, Unhealthy*, and *Dead*. By leveraging deep learning techniques, we evaluated the performance of three object detection models—YOLOv8, YOLOv9, and YOLOv11—to determine the most suitable approach for real-time plant health assessment.

Experimental results demonstrated that YOLOv11 significantly outperformed its predecessors, achieving an accuracy of 96.8%, a precision of 95.8%, a recall of 95.1%, and an F1-score of 95.4%. These findings highlight the architectural improvements in YOLOv11, enhancing its ability to accurately detect and classify plant health conditions. Additionally, we implemented a lightweight version using TensorFlow Lite, achieving an accuracy of 91%. This demonstrates the feasibility of deploying the proposed system on mobile and edge devices, making it accessible for real-world applications.

Despite its strong performance, the model’s accuracy may be influenced by dataset limitations and variations in environmental conditions. Future work will focus on expanding the dataset, improving image acquisition techniques, and integrating realtime monitoring mechanisms to enhance model robustness and adaptability.

This research contributes to automated plant health monitoring, demonstrating the efficacy of deep learning in plant classification. The proposed method has significant potential for advancing indoor plant care, supporting sustainable agricultural practices, and enabling real-time plant health assessment on lightweight computing platforms.

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