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# New plant health monitoring framework

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**Abstract.** With the continuous advancement of technology and the expanding demands of the agricultural market, plant health monitoring holds significant importance in the agricultural sector. However, according to statistics, most current monitoring models exhibit low detection efficiency and inadequate accuracy. To address these issues and specifically enhance the efficiency and accuracy of plant health monitoring, this paper proposes a recognition strategy and plan composed of two parts: (1) identification of plant species and (2) health monitoring, diagnosis, and treatment recommendations. During the health monitoring process, issues such as plant diseases, pests, nutrient deficiencies, and inadequate environmental conditions can be detected. This strategy, implemented through a systematic automated monitoring system, will greatly benefit the large-scale development of agriculture.

**Keywords:** Deep learning, Machine learning, Plant health monitoring, Object detection.

## 1. Introduction

In the context of small-scale plant cultivation and care, the survival of plants greatly influences the overall productivity and cost of the production process. Unlike lathes and raw materials on a mechanical production line, which can be maintained through regular inspections and timely replacements to ensure steady production and relatively stable output, plants require more nuanced care. The vast diversity of plant species means that the environmental conditions and other external factors suitable for different plants vary significantly. Beyond the challenges posed by their delicate growth processes and fragile existence, plants are also highly susceptible to infections from various viruses, bacteria, and pests. Any unconsidered action or minor mistake can directly or indirectly lead to a substantial decline in plant productivity or even mass die-offs, resulting in significant economic losses. Therefore, continuous monitoring of plant health to promptly identify diseases and apply effective treatments is essential to maintaining the stable and healthy condition of plants [1].

Currently, there are three commonly used methods for plant health monitoring in the market: chemical detection methods, physical detection methods, and image recognition detection methods [2-3].

Chemical detection methods primarily involve analyzing a small portion of plant tissue or the chemical composition of the soil in which the plants grow to assess plant health. This approach is based on the assumption that individual problems are generally applicable, using detailed analysis of specific cases to infer potential conditions in the remaining samples. It offers the advantage of providing detailed and clear analytical results. However, in real-world production, we cannot exclude the possibility that

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individual plants may have characteristics that significantly differ from most samples, rendering their issues non-generalizable. Additionally, the complexity and high cost in terms of time and money associated with the testing process make it impractical for most situations, whether it is for personal hobbyist-level plant testing or large-scale agricultural production. Moreover, we cannot ignore the negative impact on plants caused by collecting plant organs or tissues as samples, which raises concerns about the authenticity of the results and the generalizability of the detected problems. These uncertainties complicate future targeted adjustments, making chemical detection methods less reliable and accurate.

Physical detection methods involve assessing the physical properties of plants and comparing the obtained data against a set standard. These properties include the reflectance of plant leaves, the density, dry weight, and color of plant tissues, among others. This method benefits from the ease of quantifying and comparing test results, which greatly enhances its objectivity and evaluative capacity compared to manual assessment. However, in large-scale production, conducting basic tests on tens of thousands of plants is time-consuming and labor-intensive. Additionally, the testing tools are expensive and prone to damage, making this method less than optimal for large-scale plant monitoring. Moreover, ordinary citizens lack the means to perform such complex tests or afford the costly equipment in their daily lives. Furthermore, this method relies on having extensive data on plant diseases, setting a high entry barrier that makes it inaccessible to small and medium-sized enterprises just entering the industry, as well as individuals in everyday contexts who do not have access to the necessary standards, rendering physical detection methods unusable. Image recognition detection is capable of large-scale monitoring within a short period while requiring only simple, compact, and easy-to-maintain equipment [4]. Furthermore, a significant amount of knowledge and data is stored in binary arrays, which can be converted into user-friendly apps, making them easy to operate for both businesses and individuals with minimal learning curve. The program can also store vast amounts of data to address the potential diseases of a wide variety of plants. As the level of modernization in plant cultivation across various agricultural fields deepens, the application of image recognition technology in practice is becoming more widespread. The development of image recognition-related products holds significant industrial prospects, making further development and exploration of the technology's applications in both corporate and personal contexts highly valuable from an economic standpoint [5].

Due to its suitability for automation, image recognition methods are gaining increasing attention in smart logistics and smart agriculture. This paper focuses on image recognition methods, analyzing the shortcomings and limitations of existing methods, and proposes a new intelligent plant health monitoring detection framework. Given that the same plant disease factors can manifest differently in different plants, the proposed framework involves preliminary plant species detection, which provides plant information to enhance the efficiency of subsequent health monitoring monitoring.

The rest of this paper is organized as follows: Section II will analyze the existing methods and their limitations; Section III will introduce the new framework, which combines plant detection with plant health monitoring monitoring. Section IV will present some initial experimental results and analysis. Section V will draw the conclusion.

## 2. Background

We conducted a comprehensive analysis of related software operations to find ways to optimize app guidance in the plant care field. The software first identifies the image captured by the camera, selects the target plant, and compares it with the database of plant photos. By comparing the shape and color of the roots, stems, leaves, and the morphology of flowers or fruits, it lists possible plant species, allowing users to choose the correct plant species. Following this, by recognizing and comparing images of healthy plants of the selected species, the software determines the type of plant disease and offers suitable care suggestions and advice. The additional memo function assists users in regularly caring for and tending to the plants, improving the plants' recovery and survival rates, thereby enhancing the app's credibility and increasing user trust in the application. To improve the accuracy of plant identification, extensive data and image testing and accumulation are required. According to rough statistics, methods that rely on extensive model building and data comparison to identify the health monitoring of plants or

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fruits have been preliminarily applied and practiced in plant cultivation apps like “Xingse Yanghua” and “Ai Huacao.”

As shown in Table 1, a brief investigation and analysis of various practical apps and mini-programs reveal that these apps generally achieve accurate plant species identification by utilizing databases and basic image recognition technology. They also set up reminders for watering and other care-related tasks based on user-provided information. The active use of image recognition technology and the flexible handling and use of relevant data have greatly facilitated users’ daily lives, resolving their difficulties in accurately identifying plant species due to a lack of specialized knowledge. Moreover, most apps have effectively integrated memo functions across different disciplines, effectively meeting users’ diverse needs and potential requirements for related software. However, most apps still need further development regarding professionalization and broader application, such as disease identification. Currently, most apps require improvement and supplementation in providing reliable, professional, and personalized care plans and offering analysis and treatment suggestions for different plant diseases. They face issues of low identification accuracy, inadequate response strategies, and need to make further breakthroughs in the operability and success rate of plant disease analysis.

**Table 1.** Summary of Existing Software.

| APP | App Version Number | Comparison of Software Size(M) | Reliability | Average Processing Speed(S) |
|---|---|---|---|---|
| Flower Companion APP | v3.2.12 | 68.3 | High | 9 |
| Shape and Color APP | v3.14.21 | 9 | Upper | 8 |
| Baidu Image Recognition APP | V13.34.0.11 | 129.9 | Upper | 12 |
| Flower Recognition Master APP | v1.2.8 | 16.2 | Normal | 15 |
| Shihuajun APP | v1.1.1 | 22.2 | Upper | 13 |
| Plant Recognition APP | v2.3 | 12.33 | Normal | 14 |

## 3. The New Proposed Framework

In the current field of plant disease identification, most methods directly identify plant photos and diagnose diseases accordingly. However, the same disease-causing factors may present differently in different plants. For example, canker disease commonly found in plants manifests as holes in the trunk with exudation in poplar trees, while in tulips, it appears as yellow spots on the leaves and flower stalks. Moreover, what appear to be similar disease symptoms in different plant species may actually be entirely different diseases. For instance, apple blotch and mango anthracnose may look very similar in appearance, yet they require different treatments. Therefore, identifying the plant species before analyzing the disease can significantly improve identification accuracy and treatment efficiency.

(a) Mango Anthracnose (b) Apple Blotch

**Figure 1.** Similar Appearance of Different Diseases: (a) Mango Anthracnose. (b) Apple Blotch.

(a) Canker Disease on Poplar Tree (b) Canker Disease on Tulip

**Figure 2.** Different Manifestations of Canker Disease: (a) Canker Disease on Poplar Tree (b) Canker Disease on Tulip.

Based on the characteristics that the same pathological changes may manifest differently in different plants, and different causes of disease may exhibit similar symptoms in various plant species, we have divided the operational process into two segments to improve the accuracy of image recognition when processing plant photo data while also meeting various practical needs: the plant identification segment and the plant health monitoring monitoring segment.

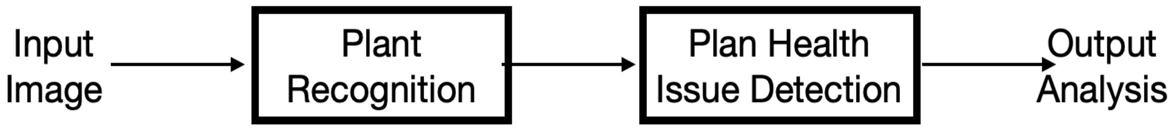


**Figure 3.** Framework of New Plant Health Issue Detection.

### *3.1. Plant Identification Segment*

Plant identification technology originates from object recognition technology. With the rapid development of computer vision in recent years, object recognition technology, as a foundational technology, has made significant advancements. Classic object recognition technologies include Region Proposals (R-CNN), Fast R-CNN, Faster R-CNN, Cascade R-CNN, Single Shot MultiBox Detector (SSD), Single-Shot Refinement Neural Network for Object Detection (RefineDet), Retina-Net, Deformable Convolutional Networks, and the You Only Look Once (YOLO) network [6-14]. Based on these classic object recognition methods, scientists and researchers have continuously released updated versions to address the limitations of each method.

Plant identification technology is a branch of object recognition. By utilizing specialized plant classification databases, existing object recognition neural networks can be trained to directly recognize plant species. In this paper, we primarily use the YOLO network.

YOLO (You Only Look Once) is an object detection algorithm proposed by U.S. Ph.D. students Joseph Redmon and Ali Farhadi in 2016. Compared to other object detection algorithms, YOLO offers higher detection speed and accuracy, which has garnered widespread attention in the field of computer vision. Since its introduction, YOLO has undergone multiple iterations, from YOLOv1 to YOLOv4, with continuous improvements in performance.

The YOLO model architecture consists of three main components: input, output, and model parameters.

(1) Input: YOLO takes an image as input and divides it into an S*S grid. Each grid cell is responsible for detecting objects whose center falls within the cell. For each grid cell, YOLO predicts B bounding boxes, with each bounding box containing the following information: center coordinates (x, y), width and height (w, h), confidence score, and class information.

(2) Output: After training, YOLO outputs S*S*B*5 values. Here, S*S represents the number of grid cells, B represents the number of bounding boxes predicted by each grid cell, and 5 represents the information contained in each bounding box: center coordinates (x, y), width and height (w, h), confidence score, and class information.

(3) Model Parameters: The parameters of the YOLO model mainly include the number of convolutional layers, the number of pooling layers, and the number of nodes in the fully connected layers. These parameters can be adjusted based on the specific requirements of the task.

The advantages of YOLO are its speed, accuracy, and adaptability. YOLO uses a forward propagation method to calculate all grid cells at once, significantly reducing computational load, thereby achieving faster runtime. By dividing the image into grids, YOLO can more accurately detect the position and size of objects. YOLO is suitable for various tasks, such as object detection, instance segmentation, and key point detection.

### *3.2. Plant Health Monitoring*

In the plant health monitoring segment, leveraging deep learning algorithms and real-time plant video surveillance, it is possible to use the effective results from plant species identification combined with the extensive knowledge of plant health research stored in the computer to evaluate the health monitoring of plants. Existing research primarily focuses on plant diseases. Plant disease is an abnormal response in plant health to a pathogen, or an organism that interferes with the normal processes of cells or tissues in a plant. Symptoms of plant disease include spots, dead or dying tissue, fuzzy spores, bumps, bulges, and irregular coloration on the fruits. The disease triangle consists of a susceptible plant, a pathogen, and favorable environmental conditions that allow the pathogen to infect the plant. Various types of plant pathogens, such as bacteria, fungi, nematodes, viruses, and phytoplasmas, can spread through different methods such as contact, wind, water, and insects. Identifying the specific pathogen responsible for the disease is crucial to implementing effective management strategies.

The plant health monitoring detection proposed in this paper goes beyond merely detecting diseases; it also includes monitoring the overall plant condition, such as detecting nutrient deficiencies and assessing moisture and light intensity levels. Through this detection method, the system can determine the plant’s health monitoring, including issues like pest infestations, nutrient deficiencies, and inadequate water or light conditions. To achieve this, neural networks are the primary technology employed. The classic Convolutional Neural Network (CNN) is a form of artificial neural network specifically designed to process pixel input and is widely used in image recognition [15].

## 4. Conclusion

After extensive research on the existing plant health detection apps available on the market, we found that all of these apps rely on directly identifying the cause of the plant’s disease, with most of them also incorporating additional features such as reminders to assist users in treatment. The integration of multiple functions greatly enhances the convenience for users. However, most apps face challenges such as low efficiency due to the complexity of the analysis process and low accuracy in identification, often resulting in mismatches between the identified plant species and the actual condition, or misdiagnosing the plant’s disease. To address these issues and specifically improve the efficiency and accuracy of plant health detection, we propose a two-part identification strategy and plan: 1) Identifying the plant species, and 2) Conducting health checks to provide diagnoses and treatment methods. During the health check process, the system can diagnose issues such as pest infestations, nutrient deficiencies, and suboptimal environmental conditions. This strategy, implemented through automated monitoring, will greatly benefit the large-scale development of agriculture.

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