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Advancements in Plant Leaf Disease Recognition: YOLO-Based Deep Learning Approaches

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Abstract: ***Plant leaf diseases cause severe losses in crop yields and qualities, and account for considerable volume of losses to the agricultural output globally. Recognition of plant disease early and rightly is crucial to disease treatment and to reduce loss to the crop and to maintain agricultural sustainability. Plant disease that occurs on the leaves has been traditionally detected by farmers and experts with naked eyes by checking its symptoms like discoloration, spots and lesions. However, the process requires time, labour, expertise and is subjective, which renders it unusable for large-scale implemented agriculture. Recent years have seen the promising use of Artificial Intelligence (AI) as a tool for automated plant disease identification. The extraction of manually-crafted features from photographs of plant leaves, such as colour, texture, and form, is at the heart of many Machine Learning (ML) approaches used for disease classification. While these ML models have shown acceptable performance, they require significant manual feature engineering and can be poor at operating in real-world settings and with voluminous data. To address these issues, Deep Learning (DL) algorithms have found extensive usage in the identification and categorisation of plant leaf diseases. The You Only Look Once (YOLO) family of detection of objects models is making waves in the DL object detection space thanks to its impressive dual-tasking capabilities: object identification and multiple illness categorisation in a single pass, all at lightning speed and with pinpoint accuracy. For real-time disease identification in precision agriculture, YOLO stands out as an end-to-end feature learning and object recognition method, set apart from typical ML approaches. Understanding the DL models suggested for plant leaf disease detection and classification using the YOLO principle is the primary goal of this survey. It also provides a comparative and performance analysis of these models by examining their techniques, merits, demerits, datasets used, and evaluation metrics.***

Keywords: Plant Leaf Disease Detection, Deep Learning, YOLO, Object Detection, Precision Agriculture, Computer Vision, Artificial Intelligence

1. Introduction

India is a country of farming where a sizable section of the populace makes their living from agriculture. Agricultural production systems are influenced by complex interactions among soil, seeds, and agrochemicals [1]. Vegetables and fruits are among the most important agricultural products, and effective quality control is essential to obtain high-quality produce [2].

Agricultural research primarily aims to increase productivity and improve food quality while reducing production costs. Several studies have shown that the quality and productivity of agricultural products can be significantly affected by plant diseases [3,4]. Plant diseases cause damage to the plants through a breakdown or interference with one or more of the plants' vital physiological processes; transpiration, photosynthesis, pollination, fertilisation, or germination [5]. Pathogens including bacteria, fungus, and viruses, together with unfavourable environmental factors, can cause these disorders [6]. Bacterial diseases are characterized by tiny, pale-green spots that gradually develop a water-soaked appearance. As the infection progresses, the lesions enlarge and eventually develop into dry, necrotic spots. Fungal diseases produce a variety of visible symptoms on plant leaves [7]. As the disease progresses, these spots become darker, and white pathogen growth may develop on the undersides of the leaves. Among plant leaf diseases, viral infections are particularly difficult to diagnose because they often do not produce distinct symptoms that can be readily identified. Moreover, viral disease symptoms can easily be confused with nutrient deficiencies or herbicide-induced injuries.

Since plant illnesses are most commonly detected on leaves, studying how to detect them early has recently been a significant area of study. Experts in agriculture and forestry, as well as farmers, have long relied on their hands-on knowledge to diagnose leaf diseases. In addition to being subjective, this process is tedious, inefficient, and takes a lot of time. During the identification procedure, less experienced farmers may make mistakes in judgement and utilise medications without thinking. In addition to causing needless economic losses, both output and quality will pollute the environment [8]. Recently, image processing techniques have been seen as a solution to these issues in the research of plant disease detection.

In order to automatically identify and analyse plant diseases, image processing is crucial. Many plant diseases manifest in the form of leaf colour, leaf texture and type [9]. These visual attributes can be obtained by digital imaging devices and can be analysed by image processing methods. Due to this, most of the plant disease detection process includes the acquisition of images, image preprocessing, segmentation of the diseased area, classification of the diseases and feature extraction. The detection of plant disease using image processing technique is demonstrated in figure 1.

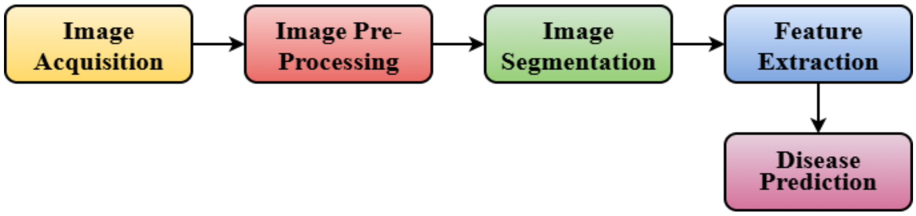

Figure 1: Image Processing Methods for the Detection of Plant Diseases

(a) Image Acquisition

Image acquisition is the first step in the process of plant disease detection [10]. Health and condition of leaves captured by digital cameras with sufficient resolution to maintain visual characteristics of the disease organism.

(b) Pre-processing Images

Improving the quality of images is the goal of image pre-processing and prepare acquired images for further analysis [11]. In this stage, unwanted distortions are reduced, noise suppression is done, target visual information is increased and diseased sections are photographed clearly.

(c) Image Segmentation

The process of image segmentation involves partitioning a leaf image into various meaningful segments and segregation of diseased tissues with health tissues of the leaf [12]. As the accuracy of the disease region extracted from the image having direct influence on the performance of feature extraction and classification, it is very important to accurately segment the image.

(d) Feature Extraction

This process of segmentation is followed by the isolation of the part of an image that contains some disease and analysing the extracted part to obtain discriminative characteristics. The visual characteristics of the damaged area are transformed into numerical characteristics, which are suitable for classification, using Feature Extraction method [13]. Color, shape and texture features are some of the common features that are extracted.

(e) Disease Prediction

Once feature extraction, the extracted colour, texture, and shape features are compared to the desired disease features or reference patterns. Using the extracted features, the disease is identified based manually defined decision rules, threshold criteria or similarity measures.

These techniques combined were used for the leaves of the healthy and the diseased. Artificial intelligence (AI) has recently found use in farming, automating the process of disease detection and classification in plant leaves. Machine Learning (ML), a major field in AI, has been used in identification and categorisation of plant leaf diseases to great extent [14]. Contrary to the traditional image processing techniques, the ML algorithms learn decision patterns from labelled training data. In the general ML plant disease classification system first process the input leaf images using various image processing techniques, then segment the diseased part, and then extract useful colour, texture, shape characteristics. These handcrafted features are then taken as input for the classifiers which are used to separate healthy leaves from various disease classes including k-Nearest Neighbour (KNN), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF) and Artificial Neural Network (ANN) [15].

Even with these benefits, the effectiveness of traditional ML approaches greatly relies on the image segmentation and hand-designed features. Some colour, texture and shape descriptors are necessary to be chosen in such a way that they provide domain knowledge and extensive experimentation is required in this case. Some features that are effective for a certain crop species, disease and imaging conditions may not be similarly effective for a different data set. Also, the difference in lightings, leaf orientations, background complexity, disease degree, and the similarity of different diseases in images may affect classification performance. There are sequential steps including classification, feature extraction, segmentation, preprocessing and feature selection that also increase the complexity of the system. Conventional ML techniques have these limitations, limiting their generalization power in larger scale and real world agricultural scenarios.

Deep Learning (DL) has been applied more and more to plant disease detection and classification in an automatic way to tackle the restrictions with handcrafted feature engineering. DL is an approach of ML that aims at hierarchically representing features on multilayer neural networks from the raw or minimally processed input data. Techniques such as Deep Belief Networks (DBNs) and Convolutional Neural Networks (CNNs) have been proposed to perform plant disease identification tasks [16,17]. These involve feeding a network with the images to learn the attributes within the images which traditional image processing algorithms may be unable to identify when looking for signs of diseases. By using extensive and complex pictures, DL models can handle high-resolution images.

However, most of the traditional DL models are limited to image classification, where they accounted for diseased leaf detection but cannot be accurate in detecting the infected areas within a whole leaf. Some object detection approaches like Faster R-CNN or SSD can also locate the object, but it is more complex and has slower inference times and hence cannot be used in real-time agriculture applications. To address these issues, single-stage models of object detection YOLOs have become an efficient approach due to their ability to extract high accuracy both on disease localization and classification and due to their real-time processing capability.

Considering the plant disease diagnosis, a remarkable study to detect it has been conducted by the family of YOLO (You Only Look Once) object identification algorithms which provide unified and real-time detection framework [19]. Unlike the more popular two-stage object detectors, which

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tackle the region generation and classification independently, YOLO casts the object detection as a single-stage prediction problem. Takes the entire input image and utilises a single network to predict the location, disease label and confidence score for each diseased region.

To classify and diagnose plant disease, this paper presents a comprehensive study of the YOLO methods. Additionally, a comparative analysis of the merits, demerits, and performance of the existing YOLO-based plant disease detection systems with the most popular dataset, performance metrics, and results are provided. Lastly, the weaknesses of current approaches, research gaps and future avenues for the creation of an accurate plant disease detection system are discussed.

The purpose of the paper is to present a comprehensive survey of a range of approaches for forecasting and detecting the leaf diseases of plants. An overview is presented to inspect the merits as well as weaknesses of these structures, thereby suggesting future directions. The following parts are structured as outlined below: In Section II, various YOLO methods that have been created for classification and estimation are examined. The third section compares and contrasts the methods. Finally, Section IV suggests the future scope and summarises the thorough survey.

2. Survey on Yolo-Based Plant Leaf Disease Detection Models

Wang et al. [20] developed a YOLOv5-based lightweight apple leaf disease detection model called MGA-YOLO. In the backbone, the conventional convolution layers were substituted with Ghost modules and C3Ghost modules to extract disease features with fewer computations. Next, a Mobile Inverted Residual Bottleneck Convolution with Attention (MBConvA) was developed by integrating the Convolutional Block Attention Module (CBAM) and used in the neck to focus on important disease features. Then, an additional prediction head was introduced to detect extra-large leaf objects.

Kumar et al. [21] developed a multi-scale YOLOv5 detection network for rice leaf disease detection. Initially, the disease-affected regions were separated using Depth-Aware Instance Segmentation (DAIS). Feature extraction from the segmented pictures was then carried out using DenseNet-201 as the backbone. The deep and shallow features that were collected were improved and combined using the Bidirectional Feature Attention Pyramid Network (Bi-FAPN) and Feature Attention Module (FAM). The multi-scale feature maps were then processed by the YOLOv5 detection head to localize and identify diseases of different sizes. Finally, a channel-pruning strategy was applied to remove less important channels and reduce the model's computational complexity.

Soeb et al. [22] suggested YOLO-T, an algorithm for detecting and diagnosing tea leaf diseases using YOLOv7. The photos were pre-processed to ensure good generalisability of the model and more picture variability. Finally, the team adopted an Extended Efficient Layer Aggregation Network (E-ELAN) as the model to extract and fuse the information of the disease-related components while simultaneously preserving the gradient flow. The features extracted were fed into the detection head which detected the position of diseases regions in the form of bounding boxes and the disease class. In addition, the model took into account the re-parameterization of convolution and auxiliary-lead detection heads which improved the disease detection.

Li et al. [23] constructed the lightweight GhostNet_Triplet_YOLOv8s model to detect leaf diseases in corn. At the first step, old backbone graph was replaced with the backbone graph: GhostNet for extracting disease features. They then removed the C2f and convolution modules and replaced them with C3Ghost and GhostNet modules, respectively, to simplify the model. To focus on clinically significant disease characteristics in both spatial and channel dimensions, a Triplet Attention mechanism (TAM) was next adopted. Lastly, to enhance the bounding-box regression and network convergence, the original CIoU loss function was modified to ECIoU loss function. In addition, the built model was used in a WeChat mini-program for real corn disease recognition.

Zhang et al. [24] developed disease detection model for apple leaves using a YOLO-ACT based on YOLOv8s. To begin, data on localised illness areas was preserved by introducing an Adjacent Feature Fusion (AFF) module that merged features from several network layers. After then, a Cascade Attention Module (CAM) took the role of the C2f module to zero in on critical illness characteristics while simultaneously decreasing background noise. Lastly, a Dynamic Task-Aligned Head (DTAH) was used to improve the interaction illness categorisation tasks, replacing the previous detection head.

Alhwaiti et al. [25] developed a fruit plant disease detection framework using YOLOv3 and YOLOv4 models. Initially, the plant images underwent pre-processing techniques like resizing, normalization and augmentation to ensure high-quality and balanced images. YOLOv3 used Darknet-53 as its backbone for feature extraction and performed multi-scale object detection through its detection heads. YOLOv4 employed CSPDarknet53 as the backbone and incorporated multi-scale feature processing to improve disease detection and localization. The predicted bounding boxes from both YOLOv3 and YOLOv4 were refined using confidence-based filtering and Reduce false positives with the use of Non-Maximum Suppression (NMS).

Kaur et al. [26] developed a YOLOv8-based YOLO-LeafNet model for multispecies plant disease detection. The images were first pre-processed, augmented and sent to the YOLO-LeafNet model for disease detection. The YOLO-LeafNet modified the YOLOv8 backbone by introducing Batch Normalization and dropout layers before the Spatial Pyramid Pooling (SPP) stage to stabilize feature learning and improve model generalization. The extracted multi-scale features were subsequently used to localize diseased regions through bounding boxes and identify the corresponding disease classes.

Li et al. [27] developed RDRM-YOLO, a YOLOv5s-based lightweight rice disease detection model. In the beginning, the backbone included a spatial depth conversion convolution

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(SPDConv) and a cross-stage partial network fusion module (Hor-BNFA) to enhance feature extraction and maintain the fine-grained characteristics of small illness spots throughout the fusion and extraction processes. In order to decrease computational complexity while keeping feature fusion capability, the standard convolution layers in the neck were substituted with lightweight GsConv.

Liu et al. [28] developed a YOLOv10n based YOLO-ALD for lightweight apple leaf disease detection. To eliminate unnecessary spatial and channel data from complicated orchard backgrounds, a Spatial and Channel Reconstruction Convolution (SCConv) was incorporated into the lower backbone layers in this case. Next, a C2f-Faster-SimAM module was developed for the neck network which combines FasterNet blocks with SimAM attention to extract subtle disease features and distinguish lesions from similar leaf-vein textures. Finally, the Focaler-ShapeIoU loss function was used in the detection head to improve the localization of irregularly shaped and difficult-to-detect lesions.

Wang and Wang [29] developed a YOLO11s based plant disease detection model called TGL-YOLO. Initially, the original feature extraction unit was replaced with a Tri-Scale Dynamic Block (TSDBlock) to extract disease features at different scales. Next, a Large-Kernel Separated Pyramid Attention (LSPA) module replaced the SPPF module to capture global contextual information. Finally, a Gated Pyramid Spatial Transformation (GPST) module was introduced in the neck to fuse cross-scale features and suppress background interference during disease detection.

3. Comparative Analysis

Table 1 compares the above-mentioned models by highlighting their merits, demerits, datasets used and their performance. The metrics employed for the performance evaluation includes, Accuracy, Precision or Average Precision (AP), Recall or Average Recall (AR), mean AP (mAP), Intersection over Union (IoU), and more.

Table 1: Summary of existing YOLO-based leaf disease detection models

Ref No	Techniques Used	Merits	Demerits	Datasets	Performance
Wang et al. [20]	MGA-YOLO, CBAM, MBConvA	The lightweight model could be easily deployed on mobile devices for real-time disease detection	The model identified only one disease when multiple diseases occurred on the same leaf	Apple Leaf Disease Object Detection dataset (ALDOD)	mAP = 94.0%, AP50 = 96.7%
Kumar et al. [21]	YOLOv5, DAIS, DenseNet-201, Bi-FAPN, FAM	The integration of deep and shallow features with an attention mechanism improved the detection of small and differently sized disease regions.	The framework had a complex architecture due to the integration of multiple models and processing modules.	Kaggle Rice Leaf Disease (RLD) dataset	AP = 82.8%, AR = 75.18%, mAP = 70.8%, IoU =0.74, Inference time = 0.017, Accuracy = 94.87%, F1-score = 92.45%
Soeb et al. [22]	YOLO-T, E-ELAN	The use of E-ELAN enabled the model to learn diverse features while preserving effective gradient flow throughout the network	The YOLO-T model required a considerably longer training time	4000 images containing five different types of leaves of tea in a customised dataset	Precision = 96.70%, Detection accuracy = 97.30%, Recall = 96.40%, F1-score = 0.965, mAP = 98.2%
Li et al. [23]	GhostNet_ Triplet_ YOLOv8s	The lightweight architecture reduced computational requirements and made the model suitable for resource- constrained devices.	The model was evaluated on only a limited number of corn leaf disease classes.	Kaggle corn disease dataset	Precision = 87.50%, Recall = 87.70%, mAP50 = 91.40%
Zhang et al. [24]	YOLO-ACT, AFF, CAM, DTAH	The model dynamically adjusted its receptive field to better localize irregularly shaped disease regions.	The added modules reduced detection speed.	PlantDoc and AppleLeaf9 datasets	AP = 84.4%, Recall = 78.6%, mAP = 85.1%, mAP50-95 = 58.3%
Alhwaiti et al. [25]	YOLOv3, YOLOv4	The study identified and located the affected regions using a single detection model, without requiring separate processing stages.	The dataset was highly imbalanced	Plant Village dataset	YOLOv3: Accuracy = 97%, F-measure = 96%, Precision = 97%, Recall = 97%, mAP = 92%. YOLOv4: Accuracy = 98%, F-measure = 99%, Precision = 98%, Recall = 99%, mAP = 98%
Kaur et al. [26]	YOLO-LeafNet	The use of Dropout layers increased the model's generalisability to unseen leaf pictures and decreased overfitting.	The inclusion of more layers had made the model more complicated.	Images of diseases in grapevines, Plant Village, PlantDoc, the Potato Disease Leaf Database (PLD), and other similar databases	Recall = 98%, Precision = 98.5%, F1-score = 98.2%, mAP50 = 0.99, mAP50-95 = 94%

Li et al. [27]	RDRM-YOLO, Hor-BNFA, SPDConv, GsConv	The model balanced accurate disease detection with a lightweight architecture, making it suitable for real-time field applications.	The model used multiple additional modules, which increased the complexity of the network design.	Rice Leaf Ailment Visual Archive (RLAVA) dataset	Recall = 89.6%, Precision = 94.3%, mAP = 93.5%
Liu et al. [28]	YOLO-ALD, SCConv, C2f-Faster-SimAM,	The model reduced unnecessary feature redundancy, enabling efficient disease detection with lower computation	The model was evaluated only on specific apple leaf diseases, which may limit its direct applicability to other disease types.	Apple Leaf Disease (ALD) dataset	Precision = 94.2%, Recall = 87.9%, mAP@50 = 92.1%, mAP@75 = 74.6%, mAP@50:95 = 63.5%
Wang and Wang [29]	TGL-YOLO, TSDBlock, LSPA, GPST	The model sustained lower computational efficiency while integrating multi-scale feature extraction	The model had difficulty detecting diseases when the affected regions were very small.	PlantDoc and FieldPlant datasets	Precision = 54.1%, Recall = 59.6%, mAP@50 = 59.1%, mAP@50:95 = 44.9%

4. Performance Evaluation

In this part, we take a look at how different DL models based on YOLO rated when it came to detecting and classifying diseases in plant leaves. The mAP obtained by the selected models is displayed in Figure 2, whereas the values of precision and recall are shown in Figure 3.

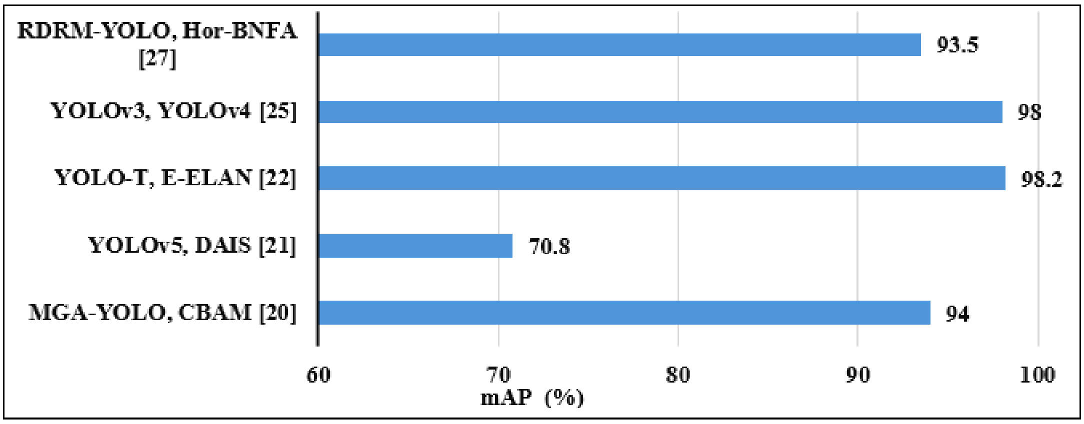

Figure 2: Performance Comparison of YOLO-Based Models Using mAP

The mAP of various YOLO-based plant disease detection models is compared in Figure 5. YOLO-T with E-ELAN proposed in [22] has the highest mAP among the tested approaches of 98.2%, which is quite close to YOLOv3 and YOLOv4 [25] with 98%. MGA-YOLO with CBAM attention mechanism [20] outperforms to attain mAP of 94% and RDRM-YOLO with Hor-BNFA [27] obtains mAP of 93.5%. YOLOv5 without the DAIS module [21] on the other hand shows the lowest mAP of 70.8%. The results demonstrate that the attention and advanced feature extraction processes are crucial for improving the accuracy of plant leaf disease detection in terms of both localisation and detection.

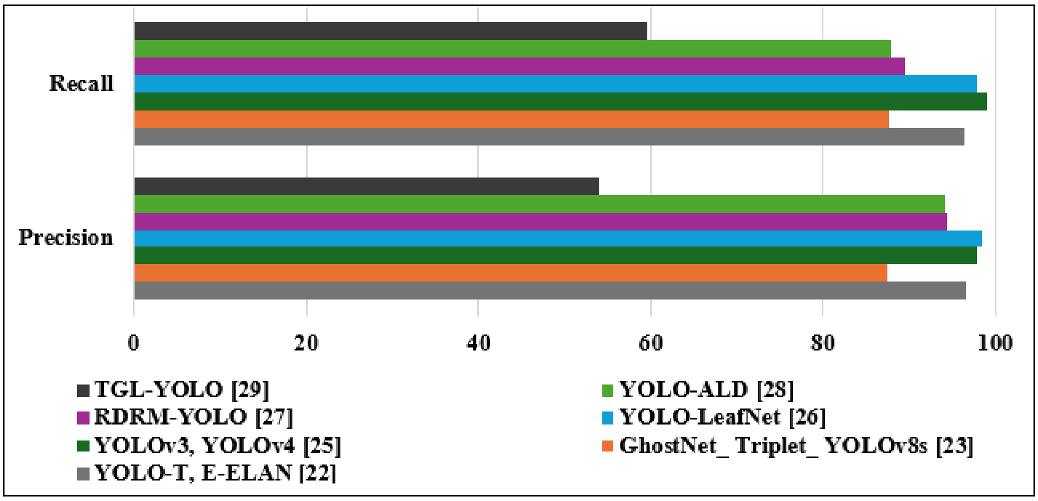

Figure 3: Comparative Analysis of YOLO models based on Precision and Recall

The recall and precision values of different YOLOs are plotted in figure 6. It is observed from the comparison that YOLOv3 and YOLOv4 have achieve the highest recall of both the models and high precision value which is almost near 99% and based on high precision value it is capable of accurately detecting the affected parts in the leaf and minimize the false detection rate to a minimal level. Good performance is obtained by YOLO-LeafNet [26] and YOLO-T with E-ELAN [22] with almost 90% precision and recall value respectively. RDRM-YOLO [27] has a score of 88% precision and 89% recall; YOLO-ALD [28] has 91% precision and 92% recall; GhostNet_Triplet_YOLOv8s [23] has 97% precision and 98% recall. Finally, the results show that the algorithms based on YOLO can also perform the accurate detection of plant leaf diseases, which can greatly improve the detection performance by using a combination of the improved backbone network, attention mechanism, and feature fusion.

5. Conclusion

Plants are important major producers of agricultural crops and detection of plant leaf diseases is important to enhance the productivity of the crops with minimum economic losses and to achieve sustainable agriculture. The present survey reveals detailed account of the methodologies, advantages and disadvantages, used data set and performance measure of the developed disease detection, disease classification and disease identification DL system based on YOLO model. From the comparison results, it can be observed that the approach in this paper based on YOLO have high detection accuracy and real time performance in implementing precision agriculture. These results provide useful information for research in the efficient and robust recognition of diseases in a large-scale leaf image database. Future work involves further exploring the model to make it more generalizable in various environments, detecting multiple diseases on one model, reducing calculation amount in the edge devices, and adding new Attention mechanism or transformer-based methods into plant diseases and their identification and crop health status tracking.

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