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aGROdet 2.0: An Automated Real Time Approach for Multiclass Plant Disease Detection

Alakananda Mitra · Saraju P. Mohanty* · Elias Kougianos

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Abstract Plant diseases prevent a plant from reaching its full potential. They are directly responsible for reducing the quality of crops and increasing the quantity of agricultural yield losses. The management, containment, and prevention of diseases depend on their precise and timely detection and severity evaluation. This paper aims to automatically detect and localize plant disease in real time. In this research, two state-of-the-art object detector-based models have been developed for disease detection and localization. Additionally, the best-performing model has been selected as the computing model of the solution, “aGROdet 2.0”, for automatic and real-time detection of plant diseases. Several publicly available datasets have been used to evaluate the solution and to avoid any bias from the datasets. A mean average precision of 91.2% has been obtained. A mobile interface has also been created to access the solution. This solution helps farmers easily detect plant diseases.

Keywords Smart Agriculture · Smart Villages · Internet of Agro Things (IoAT) · Plant Health · Plant Disease · YOLOv5 · YOLOv8 · Automatic and Real-time · Disease Detection · Localization.

A. Mitra
Nebraska Water Center at the Institute of Agriculture and Natural Resource, University of Nebraska, Lincoln
E-mail: amitra6@unl.edu.

S. P. Mohanty (Corresponding Author)
Dept. of Computer Sci. and Eng., University of North Texas
E-mail: saraju.mohanty@unt.edu

E. Kougianos
Dept. of Electrical Engineering, University of North Texas
E-mail: elias.kougianos@unt.edu.

1 Introduction

Agriculture plays a significant role in the global food supply chain and economy [1]. However, various conditions like climate change, rapidly increasing population, over exploitation of natural resources, natural calamities, and plant diseases adversely affect the crop yield. Plant disease affects the crops qualitatively and quantitatively, resulting in billions of dollars in financial losses [8]. An on-time and accurate detection of the disease can prevent its spread and help farmers take control measures, which has economical and environmental benefits and thereby avoids significant economic losses.

Plant diseases are conditional on the time of the year and kind of vegetation and can be prompted by either environmental factors or live organisms. Plants can contract biotic diseases from fungal, bacterial, viral, and algal pathogens, as shown in Fig. 1, as well as abiotic diseases from factors such as lack of nutrition, extreme temperatures, excessive moisture, and sudden temperature changes. Diseases can appear in different parts of the plant, from stems to fruits, and can occur at any stage during a plant’s development [56]. Discoloration, shape shifts, wilting, galls, spots, mildew, and cankers are all possible symptoms [37].

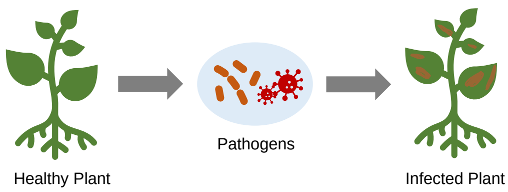


Fig. 1 Biotic Disease Infection.

Traditionally, domain experts or plant pathologists used to identify the disease by visually examining the infected leaves [74]. This method, however, is very time-consuming and labor-intensive [78]. The accuracy of this process also depends on the experience and proficiency of the experts. This type of expert service is either not always available to the smallholder farmers in remote villages or they are expensive. Thus, it creates a burden to the smallholder farmers' finances. An automatic detection system that can identify plant diseases is a suitable alternative to such labor-intensive and expensive work.

Various computer vision and image processing techniques [33,67,71,75] have been explored and developed over the years to detect and identify plant diseases. Deep Learning, a sub-field of machine learning, has grown in prominence. Deep learning techniques automatically extract high-level data features during training and provide high accuracy in various computer vision and natural language processing tasks. They are now extensively [15, 16, 18, 20, 32, 50, 53, 59] employed in plant disease identification.

1.1 Challenges in Detecting Plant Disease

Automated plant disease detection faces several challenges:

1. The similarity of symptoms between diseases [25,35] makes the detection process difficult.
2. At various stages of disease, symptoms may vary. For example, *leaf spot* disease appears as little purple dots, but the small dots change into circular spots of quarter inch diameter and with a black center spot [6]. Large scale data collection which covers every stage of a disease is needed.
3. Variation of humidity, soil water content, temperature, rainfall, CO_2, C and N content in soil vary and cause abiotic stress induced symptoms [86] along with diseases caused by biotic stress.
4. Plant images, captured in uncontrolled settings like field, orchard/vine, difference of illumination [61], shadow [64, 66], angle of capture [88], presence of pests, or disease residues make the detection process complex.

1.2 Problem Addressed in the Current Paper

This article aims to identify plant diseases automatically and in real time so that even smallholder farmers in remote villages can perform accurate disease identification on their own.

1.3 Proposed Solution

In this research, we propose a novel method to automatically, and in real-time detect plant diseases without any expert service. The solution is capable of detecting the disease from image and video of the infected leaves. Two state-of-the-art object detectors that can detect an object from a real time video, have been evaluated to select the object detector for "aGROdet 2.0". However, leaf images have been used for the experiment. The current solution assists farmers with the automated detection of plant disease so that the necessary actions can be taken on time. The solution can be accessed through a mobile interface.

1.4 Major Contribution of the Current Paper

The main contributions of the current work are as follows:

- The proposed object detection-based approach precisely localizes the infected leaves along with disease detection. It is easily accessed through the mobile interface "aGROdet".
- It is capable of detecting all the infected leaves of an image.
- The method is fully automated as disease detection is done using images of the leaves. Therefore, no expert guidance is required for disease detection.
- Faster evaluation of the disease without paying an expert guidance service fee is also possible as there is no delay involved in securing an expert's time.
- It provides a real time solution which helps farmers to promptly take control measures.
- Extensive performance analysis has been performed using three publicly available datasets which consist of images taken at uncontrolled environments. It proves the robustness of the approach.

The rest of the paper is organized in the following order: Section 2 presents recent work on plant disease detection. In Section 3, the proposed method for plant disease detection is described. Section 4 presents the experiments and the mobile interface. Section 5 demonstrates the results and evaluates the performance of the method. A comparative analysis with existing research is also presented. Finally, the current paper is concluded with suggestions for future work in Section 6.

2 Prior Research Work

Machine learning and deep learning technologies supported by various embedded systems [29], graphical processing units (GPU), tensor processing units (TPU), AI-accelerators, edge processors, and IoT sensors have all changed the traditional, arduous, and time-consuming plant disease detection to more accurate, fast, and easy detection. In recent years, machine learning and deep learning techniques are predominantly being used in plant disease detection. Computer vision is being largely employed for this. Various image-based datasets have been proposed for different plants, crops, and fruits. Some are in laboratory settings [36] and some are in normal field settings [28]. In this section, works related to plant disease identification, localization, and tracking are presented.

2.1 Machine Learning-based Approaches

Among various approaches of plant disease detection, machine learning-based approaches have gained popularity among the research community for a long time, even before the monumental growth in deep learning technologies. Table 1 describes several of the works which are machine learning based. Support vector machines (SVMs) and K-means clustering are the two most commonly used classifiers in detecting various plant diseases. These classifiers have been used separately [11,12, 72,76] or in combination with other methods [46,84,85].

A multi-class SVM has been used to classify grape leaf diseases like black measles, black rot, and leaf blight in [38]. Leaf areas affected by the disease have been extracted with K-means clustering. Feature dimension reduction by principal component analysis (PCA) resulted in better accuracy than gray-level co-occurrence matrix (GLCM) features. However, the use of the PlantVillage dataset renders the methods not really applicable to real life scenarios.

K-means clustering with a rule-based system has been used in [43] to classify between healthy leaf and infected soybean leaf. Downy Mildew, Frog Eye, and Septoria Leaf Blight have been classified with an SVM classifier. However, the paper is unable to provide an automatic method for plant disease detection.

Another effort was made in [60] to automatically diagnose plant diseases using leaf images. Local binary patterns (LBPs) and one-class classification retrieved leaf features. The algorithm improved with each new image. This approach recognized new diseases and interpreted them as a new reference section. However, deep learning-based systems provide better accuracy than ML classifiers and the feature extraction process is automatic.

2.2 Deep Learning-based Approaches

In the last few years, more works on plant disease detection using deep learning technologies are being published. This is due to the high accuracy achievable through these networks. The majority of the works are computer vision based and use convolutional neural networks (CNNs). Three types of solutions are provided: *classification*-based, *object detection*-based, and *image segmentation*-based.

2.2.1 Classification-based Approaches

Deep neural networks, especially CNNs, are predominantly used in classification-based methods. CNNs vary from custom CNNs to well known CNNs. This section describes some recent plant disease classification research. Corn Rust and Northern Leaf Blight along with healthy corn leaves have been classified in [51] using custom CNNs. Some field corn leaves images have been used with corn leaves of the PlantVillage [36] dataset. In [87], a global pooling dilated CNN has been used for six cucumber leaf diseases identification, whereas the authors in [44] used well known CNNs and Entropy-ELM-based feature selection methods to classify the disease.

CNNs extract the features from an image automatically and those features are classified using various classifiers. Compared to traditional machine learning methods, which rely heavily on image processing, these new methods are significantly more effective [79]. Apple leaf diseases have been identified with a combined EfficientNetB4 and attention network [80], DenseNet and XceptionNet as a feature extractor, and finally classification through SVM [22], an ensemble of pre-trained DenseNet121, EfficientNetB7, and NoisyStudent networks [17]. These processes have achieved high accuracy. SSD with Inception and Rainbow concatenation [40] structure has also been used to detect five types of apple diseases. The proposed model has achieved 78.8% mean average precision (mAP).

A modified Inception structure identified grape leaf diseases in [47]. Dense connectivity with the Inception structure improved the features. Data augmentation has also increased the dataset size. The accuracy of the method is moderate compared to the existing works.

Well known and well performing CNNs are predominant in disease detection [16, 18]. The use of custom CNNs [15, 20, 32, 50] is also a very popular preference among researchers. In both cases, the CNN is mostly used for automatic feature extraction and SVM [23,39], MLP [49], Softmax [34], etc. are used as the classifier.

Table 1 Prior Research Works on Plant Disease Detection

Papers	Year	Crop	Methods	Remarks
Kaur, et al. [43]	2018	Soybean	K-means clustering + SVM.	Not fully automatic.
Ma, et al. [50]	2018	Cucumber	DCNN	Field Data has been used.
Picon, et al. [62]	2019	Wheat	Deep Residual Neural Network	Three types of wheat diseases have been detected. Tested the method in different mobile devices,
Liu, et al. [48]	2020	Tomato	Improved YOLOv3	Twelve types of tomato diseases/pests have been identified.
Jiang, et al. [39]	2020	Rice	CNN + SVM	Four types of rice diseases have been detected along with healthy leaf.
Ng, et al. [59]	2021	Grape	Faster R-CNN with InceptionV2 backbone	Grape leaves infected with three types diseases along with healthy leaves have been detected.
Chen, et al. [24]	2022	Plants	CACPNET	Peanut field data has also been used with PlantVillage dataset.
He, et al. [34]	2022	Plants	DIR-BiRN	Use of PlantVillage dataset makes the methods far from real life scenarios.
Liu, et al. [49]	2022	Tomato	DCCAM-MRNet	Six types of tomato diseases have been identified. Field data has been used.
Borhani, et al. [19]	2022	Plant	Vision Transformer	The method has been evaluated with three different datasets.
Khan, et al. [44]	2022	Cucumber	CNN + Entropy-ELM Feature Selection	Six diseases have been detected.
Mitra, et al. [54]	2022	Plants	Custom CNN + Pixel-based method	Automatic detection and localization of plant diseases.
Javidan, et al. [38]	2023	Grape	SVM + K-means clustering + PCA	Use of PlantVillage dataset makes the methods far from real life scenarios.
aGROdet 2.0 (Current Paper)	**2023**	**Plants**	**YOLOv8**	**Real time and automatic detection of plant diseases.**

DCNN → Deep Convolutional Neural Network; DIR-BiRN → Disease Image Recognition-Bilinear Residual Networks; DCCAM-MRNet → Dilated Convolution and Coordinate Attention Mechanism Mixed Residual Connection Network; CACPNET → Channel Attention and Channel Pruning Network.

Despite being able to correctly identify the diseases with high accuracy, CNN-based classification does not localize the disease. However, the extent of the disease, can be determined from the percentage of damage. Image segmentation-based approaches are suitable for that.

2.2.2 Image Segmentation-based Approaches

The second type of approach is image segmentation based. It is basically a *regions-of-interest* (ROI) deep CNN. This type of detection has two stages. In the first stage, object regions are proposed and in the second stage classification is done from those features and localized with bounding boxes.

Using several ROI based structures, nine distinct pests and diseases of tomato plants were identified in [30]. In certain circumstances, data augmentation has increased mAP by as much as 30%. A faster R-CNN has been used with an InceptionV2 backbone to detect grape leaf diseases [59]. The model runs on a smartphone with 97.9% accuracy. Faster R-CNNs have also been used to identify rice false smut disease [73], tomato diseases [81], and diseases of five different plants [26].

Mask-RCNN has been used to detect wheat mosaic virus [45], strawberry diseases [13, 14], and apple leaf diseases [53]. Articles also employ multiple ROI-based formats. Faster R-CNN and Mask R-CNN were applied to identify and detect diseased segments in [82]. Mask R-CNN and ensemble subspace discriminant analysis classifiers were employed to detect infected apple leaves in [70]. However, as these image segmentation-based approaches have two stages, they are slower than one-stage detectors [5]. Table 2 [21] indicates how the inference time differs for one-stage and two-stage detectors. The lowest inference times for both high and low resolution images are for one-stage detectors.

2.2.3 Object Detection-based Approaches

The third type of disease detection is object detector based. These approaches can localize the disease along with precise identification using single stage object detectors. As in these types of object detectors, any number of objects are found and classified using a bounding box in a single stage, it takes less time to detect objects. Hence, this type of object detector is used for various real time object detection applications.

Anthracnose lesion on apples has been detected using the YOLOv3 network [77]. To improve the result, DenseNet has been used as the backbone feature extractor in YOLOv3. The image dataset has been expanded using traditional data augmentation techniques and CycleGAN [89]. The DF-Tiny-YOLO structure was introduced in [27] to identify diseases in apple leaves. The use of smaller CNN kernels accomplishes these goals by decreasing the number of dimensions in the features being used and by increasing the depth of the network without increasing its complexity. Various versions of YOLO [48,57] have been used in detecting various plant diseases.

2.3 Gaps in the Existing Solutions

The above discussion presents several research studies in the plant disease domain. They have their own strengths and weaknesses.

- Classification-based approaches only identify the disease; they do not localize it. Therefore, these methods cannot provide any information on disease severity.
- Object detection and image segmentation-based approaches, on the other hand, localize the disease as well as identify it. Image segmentation-based approaches can provide more precise information on disease severity than object detector-based methods. However, image segmentation-based approaches demand more computational power.
- The majority of the papers do not use field datasets, which makes them perform poorly with field data.
- Due to the rapid growth of deep learning technologies and AI-assisted embedded systems, solutions with state-of-the-art networks, capable of keeping pace with technological progress, are required.
- To take any control measures, rapid and on-time disease detection is necessary. More research on methods which are efficient, smaller in size, and can infer faster is needed. Hence the disease can be detected in real time while taking the photo/video of the infected plants/trees.

In summary, more research focusing on real time disease detection is necessary, which will eventually help in early detection and automatic tracking of the disease.

3 Model and Methodology

3.1 Overview

As mentioned in Section 2, among the various plant disease detection approaches, the object detection-based approach has the advantage of localizing the disease, along with identification. Object detection is a computer vision technique that is used for counting objects, tracking object location, and accurately identifying objects in an image or video frame.

In this research, to identify the plant disease in real time, we used an efficient, fast, small-sized deep learning model. Initially, we chose two different members of the “You Only Look Once” (YOLO) [68] family to experiment with. Two state-of-the-art object detectors, YOLOv8 [41] and YOLOv5 [42] have been used to detect and localize the plant diseases, and their performance has been compared to select the final model. Instead of a controlled environment using datasets [53,54], field data and data collected under the sun, have been used. These scenarios match real-world environments. The selected model is the core computing component of the solution, “aGROdet 2.0.”

Fig. 2 shows an overview of “aGROdet 2.0”. If any plants are infected with diseases, farmers capture images of the infected leaves using the mobile interface of “aGROdet 2.0”. It then predicts the disease. The details of the mobile interface are discussed in Section 4.5.

The proposed YOLO object detector-based detection method detects the disease from the full image in only one evaluation and with only one forward pass. The network breaks the image into regions/grids and predicts bounding boxes and probabilities for each region. The predicted probabilities are used to give these boxes weights. This process is very fast and it does not need a complex operational pipeline. Hence, it is suitable for real time disease detection of large crop fields. The small size and high efficiency of the YOLO models make them suitable for implementation in edge computing hardware. The different versions of each member of

Table 2 Inference Time Comparison between One-stage and Two-stage Object Detectors [21]

Stage	**Architecture**	**Feature Extractor**	Image Resolution	**Inference Time (ms)**
Two	Faster RCNN	FPN ResNet50	High	105.09
			Low	48.00
One	Fully Convolutional One-Stage Object Detection	FPN ResNet50	High	95.00
			Low	42.25
One	RetinaNet	FPNLite + MobileNetV2	High	63.20
			Low	**26.12**
One	YOLOv3	DarkNet-53	High	**70.81**
			Low	40.19

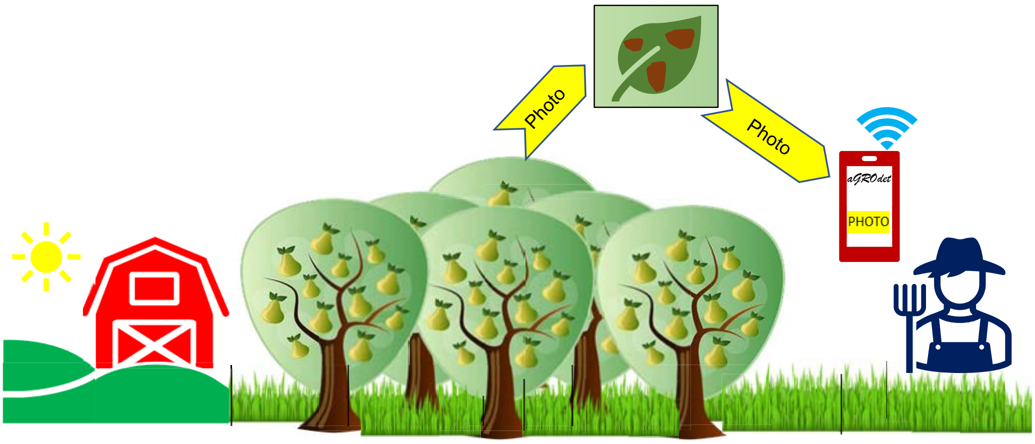


Fig. 2 Overview of aGROdet 2.0.

YOLO, namely nano, small, medium, larger, and extra large allow them to scale for any type of crop field. However, the scaling part has not been addressed in this article.

3.2 Model Architecture for Disease Detection and Localization

3.2.1 YOLOv5

It is the fifth member of the YOLO family. There are a total of five variants of it: nano, small, medium, large, and extra large. Accuracy increases with the size of the models. The smaller the model size, the shorter is the training time. In our work, the medium version (YOLOv5m) has been used.

The idea of the YOLO models is to connect class labels with bounding boxes in an end-to-end differentiable network. Here, a single CNN predicts bounding boxes with class probabilities [68]. YOLO has three primary components:

- Backbone: CSP-Darknet53 serves as the backbone for YOLOv5. CSP stand for Cross Stage Partial. It extracts the features from the image.
- Neck: It uses a variant of Spatial Pyramid Pooling (SPP) as the neck. It helps the network to perform accurately on unseen data. The Path Aggregation Network (PANet) has been modified by including the BottleNeckCSP in its architecture.
- Head: Uses neck features for box and class prediction. The same head as YOLOv3 and YOLOv4 is used by YOLOv5. It is made up of three convolution layers that predict where the bounding boxes (x, y, height, and width), objectness scores, and object classes will be.

The following equations [42] are used to calculate the target bounding boxes in YOLOv5:

$$b_x = (2 \cdot \sigma_(t_x) - 0.5) + c_x \tag{1}$$

$$b_y = (2 \cdot \sigma_(t_y) - 0.5) + c_y \tag{2}$$

$$b_w = p_w \cdot (2 \cdot \sigma(t_w))^2 v \tag{3}$$

$$b_h = p_h \cdot (2 \cdot \sigma(t_h))^2 \tag{4}$$

Fig. 3 shows the terms appearing in these equations. b_x, b_y, b_w, b_h are the center, width, and height of the predicted bounding box, t_x, t_y, t_w, and t_h are the outputs of the neural networks, c_x and c_y are the cell's top left corner of the anchor box, and p_w and p_h are the anchor's width and height.

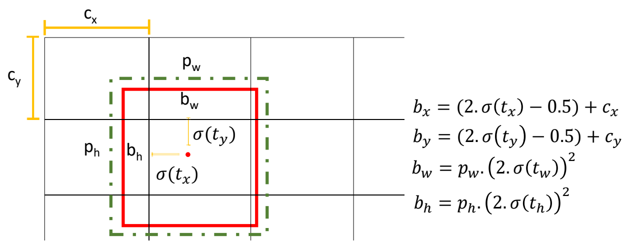


Fig. 3 Equation formulation for the target bounding box in YOLOv5 [69]

Binary Cross Entropy loss is used to calculate class loss and objectness loss whereas Complete Intersection over Union loss is used to calculate location loss. YOLOv5 uses logistic regression to predict the confidence score of each box. Hence, each box predicts the class type associated with the bounding box using multilevel classification.

When the network sees a leaf for the disease detection, the image is divided into $S \times S$ grids. The grid cell contributes in detecting when the center of the object falls on that grid. For each grid cell, bounding boxes and confidence scores are predicted. No object means zero confidence score. The intersection over union of the predicted bounding box and the ground truth bounding box calculates the confidence scores [68].

3.2.2 YOLOv8

The newest member of the YOLO family is YOLOv8 [41]. This state-of-the-art model is used for instance segmentation along with classification and object detection. The biggest difference between YOLOv8 and the other YOLO models is its anchor-free nature. It directly predicts the center of an object rather than the offset from a known prior or anchor box. As a result, the number of box predictions have been reduced and the overall system becomes faster by speeding up the Non-Maximum Suppression [10]. Architecture-wise there are certain modifications: the earlier C2f module is replaced by the C3 module, the first 3×3 conv in the bottleneck is changed to 6×6, and the first 1×1 conv in the bottleneck is replaced by 3×3. Without mandating channel dimensions, neck features are fused directly. The YOLOv8m variant has been used in our work. Table 3 describes the structures of the YOLOv5m and YOLOv8m models.

Data augmentation plays a significant role in YOLOv5 and YOLOv8 training. One of these is mosaic augmentation. This is done by putting together four images, which forces the model to learn how to recognize objects in new places, with partial occlusion, and against different pixels around them.

4 Experimental Validation

In this section, our proposed plant leaf detection method has been evaluated with two state-of-the-art object detectors, YOLOv8 and YOLOv5, and three publicly available datasets. In both cases, the medium variants of the model have been used. In our initial work [53], the PlantVillage dataset [36] had been used. However, images in the PlantVillage dataset are taken in laboratory settings. So, they are far from the real world data and the model does not perform well with real life field data when it is trained on it [36]. To avoid this issue, different settings datasets, e.g., field data, samples extracted from the field but photo was captured in the sunlight with a more structured environment, and the laboratory settings images, have been utilized in this work. Fig. 4 describes the total experimental process.

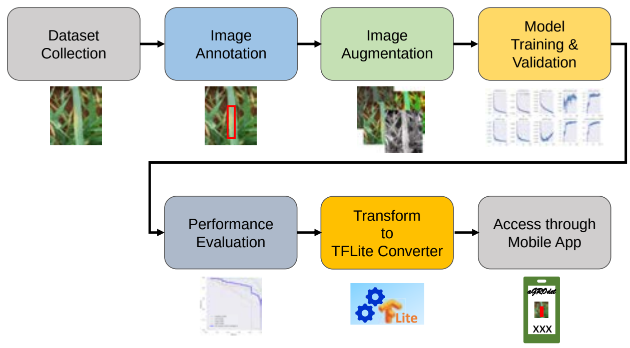


Fig. 4 aGROdet 2.0 Developmental Workflow

4.1 Dataset

Three different datasets have been used to select the perfect object detector model for the aGROdet 2.0 framework. The datasets are described in Table 4.

4.1.1 DiaMOS Plant Dataset

This dataset [28] contains a total of 3505 images of pear leaves and fruits. It was published in 2021. Among the 3505 images there are 3006 leaf images and 499 fruit images at various stages of growth. Images of three pear diseases: Spot, Curl, and Slug and healthy pear leaves are included in the leaves section of the dataset. The fruit section consists of four phases: fruit set, nut fruit, fruit growth and ripening [28]. The photos were captured using a Honor $6\times$ smartphone and a Canon EOS 60D camera. Images are of two resolutions: 2976×3968 and 3456×5184. Fig. 5 shows sample images of each class.

Table 3 Comparison between YOLOv5m and YOLOv8m.

Model	No. of Layers	No. of Parameters	Size (MB)	No. of GFLPOS
YOLOv8m	295	25858057	52.0	78.7
YOLOv5m	291	20879400	42.1	47.9

Table 4 Dataset Details

Dataset Name	Publication Year	Dataset Details
DiaMOS Plant [28]	2021	3 pear diseases: Spot, Curl, and Slug + healthy pear leaves. Total 3006 leaf images and 499 fruit images at various stages of growth.
Wheat Leaf [31]	2021	2 wheat diseases: Septoria and Stripe Rust + healthy wheat leaves. Total 407 images.
Rice Leaf Disease [9]	2017	3 rice leaf diseases: Bacterial Leaf Blight, Brown Spot, Leaf Smut. Total 120 images.

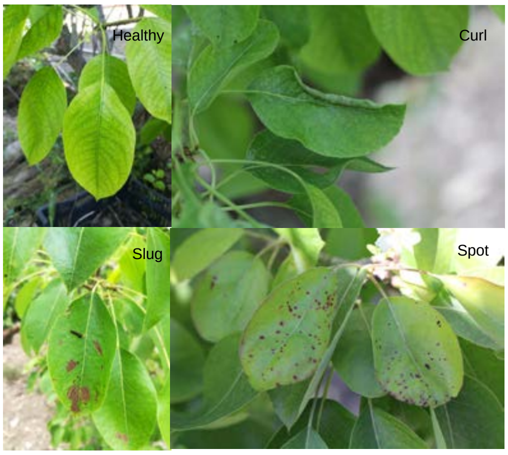


Fig. 5 Sample Images from DiaMOS Plant Dataset

4.1.2 Wheat Leaf Dataset

The second dataset is the *Wheat Leaf* dataset [31]. The dataset has a total of 407 images. It has three categories: *healthy* wheat leaf, *Septoria* disease infected wheat leaf, and *Stripe rust* disease infected wheat leaf. There are 102 *healthy* leaves, 97 *Septoria* affected leaves, and 208 *Stripe rust* affected leaves in the dataset. A Canon EOS 5D Mark III was used to capture those images at the Holeta wheat farm, Ethiopia. These images are real field data captured in an uncontrolled environment. Fig. 6 shows sample images of the three classes.

4.1.3 Rice Leaf Disease

This dataset [9] contains 120 images of three rice leaf diseases: *Bacterial Leaf Blight*, *Brown Spot*, and *Leaf Smut*. These diseases usually affect leaves. When a plant is infected with *Bacterial Leaf Blight*, several inches of yellow and white elongated lesions are visible on the leaf tip. Brown Spots are circular or oval in shape and vary in color from dark brown to reddish brown. *Leaf Smut* are spread all over the leaf and are usually

Fig. 6 Sample Images from Wheat Leaf Dataset

smaller in size than *Brown Spots*. They are also reddish brown in color [65]. The images were taken with a white background under the sun with a Nikon D90 digital SLR camera with 12.3 megapixels from a village named Shertha in the Western part of India. Sample images of each class from the dataset [9] are shown in Fig. 7.

Fig. 7 Sample Images from Rice Leaf Disease Dataset

Table 5 summarizes various aspects of pear, wheat, and rice leaf diseases: crop name, disease name, full name of the disease if different from the common name, type of the pathogen, name of the pathogen, and the symptoms of the disease.

Table 5 Details of the Diseases

Crop Name	Disease Common Name	Disease Full Name if otherwise	Caused By	Pathogen	Symptoms
Pear	Curl	–	Variety of reasons.	–	Leaf curling.
Pear	Slug	–	Sawfly	Caliora cerasi	Inner tissues of the leaf gets exposed. Finally, the leaf dries and changes to brown color.
Pear	Spot	–	Fungus	Fabraea maculata	Brown spots on the leaf.
Wheat	Septoria	Septoria tritici blotch (STB)	Fungus	Mycosphaerella graminicola	Necrotic lesions on leaves and stems. [63]
Wheat	Stripe Rust (Yellow Rust)	–	Fungus	Puccinia striiformis	Small, round, tightly packed on seedling leaves and yellow stripes on mature plants. [58]
Rice	Bacterial Leaf Blight	–	Bacteria	Xanthomonas oryzae	Initial symptoms water-soaked lesions at leaf edges and tips. Finally, grayish-white leaf lesions and leaf drying. [2]
Rice	Brown Spot	–	Fungus	Cochliobolus miyabeanus	Initial small, circular yellow ir brown lesions change to large circular or oval leasions with reddish brown margin. [3]
Rice	Leaf Smut	–	Fungus	Entyloma oryzae	Slightly elevated angular, black spots.

4.2 Image Annotation

An important stage in object detector training is the annotation of images with ground truth. In the training datasets, bounding boxes are drawn across the objects. MakeSense.AI [4], an open source image annotation tool, was used to annotate the data, and the *Rect* tool was utilized to annotate images. Annotation files are saved in ".xml" format and provide the coordinates of the bounding box's two diagonally placed corners. Different colors are used for different classes when labeling. The DiaMOS Plant dataset already contains annotation for YOLO models. However, the Wheat Leaf and Rice Leaf Disease datasets have been annotated by us.

4.3 Image Augmentation

Default image augmentation techniques: HSV adjustment, translation, scaling, left to right flip, and mosaic augmentation have been used. For better performance, mosaic augmentation is turned off for the last ten epochs for YOLOv8. The data augmentation parameters are kept as default: Blur parameter p is set to 0.01 and *blur_limit* to $(3, 7)$, MedianBlur parameter p to 0.01 and *blur_limit* to $(3, 7)$, ToGray to 0.01, CLAHE parameter p to 0.01 and *clip_limit* to $(1, 4.0)$, *tile_grid_size* to $(8, 8)$. 8 data loader workers have been employed for YOLOv8 and 2 for YOLOv5.

4.4 Training

The networks have been trained on a system with an NVIDIA Tesla T4 GPU, 25.5 GB system RAM, and 15 GB GPU RAM. PyTorch has been used as the deep learning framework. We followed the procedure in [41, 42]. The models were trained for 100 epochs (YOLOv8) and 150 epochs (YOLOv5). A Stochastic Gradient Decent optimizer with a default learning rate of 0.01 has been used. Batch sizes were kept at 32 for YOLOv8 and at 16 for YOLOv5.

4.5 aGROdet 2.0 Mobile Interface

The development of the "aGROdet 2.0" mobile interface has been done in Android Studio IDE using JAVA. The Nexus 5 API 30 emulator has been used to emulate the application.

Fig. 8 shows the application interface. The leftmost figure in Fig. 8 shows the first screen. Using the "PHOTO" button, the user can take a picture of the plant leaf. Once the photo is captured, the "DETECT" button allows the user to show the result.

For our experiment, images stored in Google Drive have been used. When the "PHOTO' button was pressed, the image from the drive was selected instead of actual field photo capture. However, this interface will be updated in future work, when a video option will also be available.

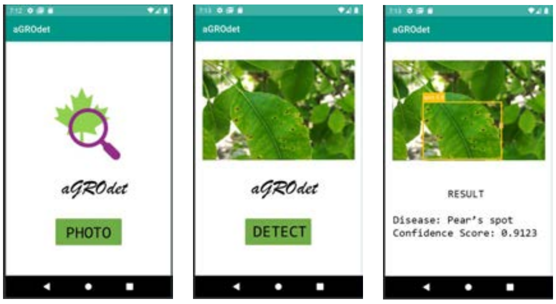


Fig. 8 Disease Detection through the aGROdet 2.0 Mobile Interface.

5 Performance Evaluation

5.1 Performance Metrics

To evaluate the performance of the framework, several performance metrics have been calculated for the two object detectors using the aforementioned datasets. The metrics calculated are: *precision*, *recall*, *f1-score*, IoU, and mAP [52].

Precision describes how many of the confirmed identifications turned out to be accurate. It is defined as:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Recall states the percentage of true positives that were correctly classified as being positive. *Recall* is defined as:

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

F1-score measures the model's accuracy on the dataset. It is defined as:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

Intersection over Union (IoU) measures the overlap between predicted boundary and ground truth boundary as in Eq. 8.

$$\begin{aligned} IoU &= \frac{Area\ of\ Intersection}{Area\ of\ Union} \\ &= \frac{TP}{TP + FP + FN} \end{aligned} \tag{8}$$

In the above expressions, TP, FP, TN, and FN are *true positive*, *false positive*, *true negative*, and *false negative*, respectively. The average precision changes based on the IoU threshold value. IoU varies from 0.5 to 0.95.

The area under the precision and recall curve defines the *average precision* of the object detector. mAP is calculated from the *average precision* AP_i using Eq. 9:

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i, \tag{9}$$

where N is the total number of classes. mAP takes into consideration both false positives (FP) and false negatives (FN) and considers the trade-off between *precision* and *recall* [53]. Because of this, mAP is an excellent metric for detection tasks. The validation dataset has been used to evaluate the model.

5.2 Results

In this section, the performance of "aGROdet 2.0" is described and analyzed with regard to both the object detector models and all the datasets.

5.2.1 YOLOv5

Performance Metrics of YOLOv5 have been plotted in Fig. 9(a) - 9(l) for different datasets. The first column shows the metrics plot for the DiaMOS Plant dataset, the second column is for the Wheat Leaf dataset, and the third column is for the Rice Leaf Disease dataset. The Precision vs. Confidence plot has been shown in Fig. 9(a) -9(c). Fig. 9(d)- 9(f) show the Recall vs. Confidence plot. Fig. 9(g)- 9(i) are the Precision and Recall plots. Fig. 9(j)- 9(l) show the F1-Score vs. Confidence plots.

YOLOv5 has shown higher *precision* for the Wheat Leaf and DiaMOS Plant datasets than the Rice Leaf Disease dataset. Higher *recall* has been achieved for DiaMOS Plant and Rice Leaf Disease datasets. Higher number of FP has lowered the *precision* of YOLOv5 model in the case of Rice Leaf Disease datasets. In several cases of Bacteria_leaf_blight and Brown_spot are wrongly predicted as Leaf_smut disease. Similarly, lower *recall* has been attained for the Wheat Leaf dataset because of higher number of FN. When the IoU threshold value is set to 0.5, the highest mAP of 0.894 has been achieved for DiaMOS Plant dataset. The *F1-score* of YOLOv5 is also highest for DiaMOS Plant dataset. This is due to the higher number of training data in DiaMOS Plant dataset. In Rice Leaf Disease dataset, the leaves are placed on white paper and the image was taken under the sun. Each image contains a single leaf.

Table 6 describes how *mAP50* of YOLOv5 model varies with image size for different datasets. It shows that when the image size is 640×640, YOLOv5 achieves better mAP in case of Wheat Leaf and DiaMOS Plant datasets. Hence, we chose an image size of 640×640 during performance comparison of YOLOv5 and YOLOv8.

Fig. 10(b) shows the predicted results of the ground truths of Fig. 10(a). These samples are from the DiaMOS Plant dataset.

There are certain cases in the DiaMOS Plant dataset when there are discrepancies in detecting the disease.

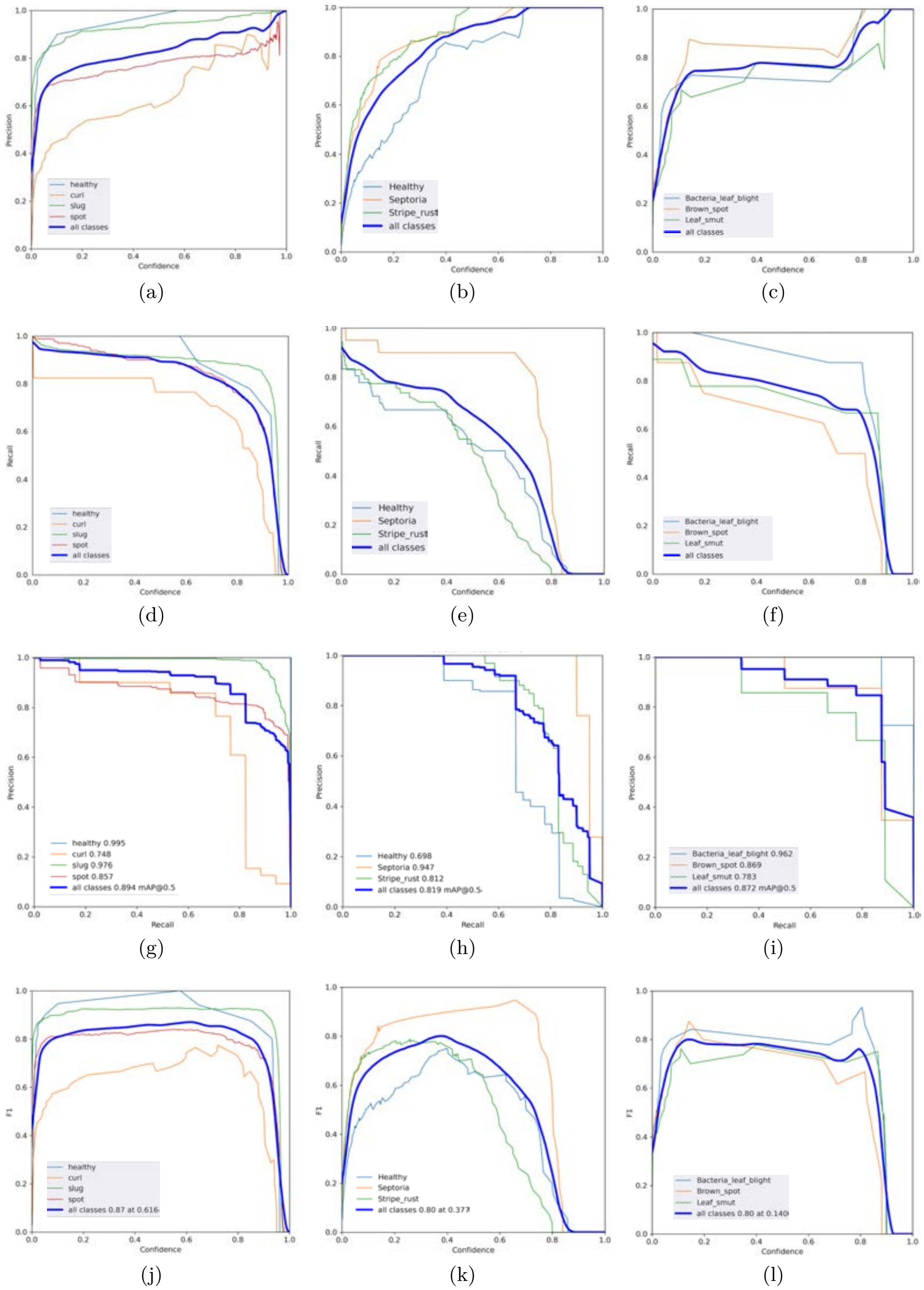
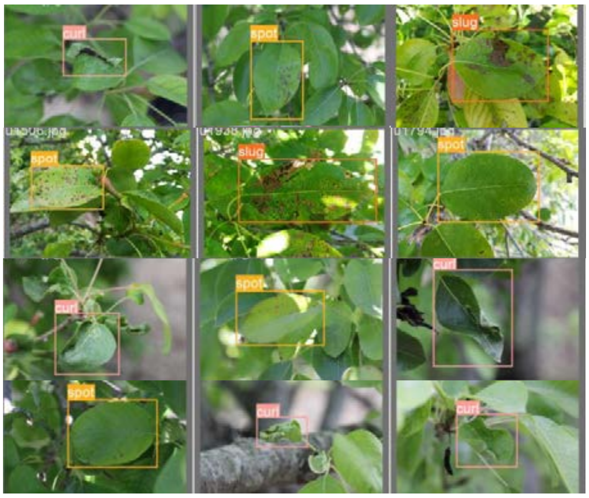


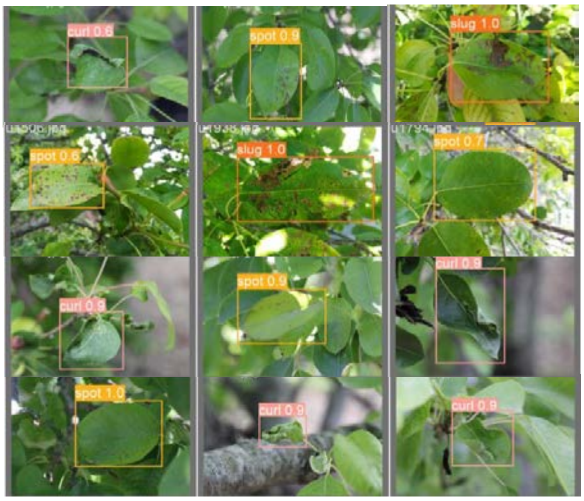
Fig. 9 Performance Metrics Plots of YOLOv5 for different datasets. (a)-(c) Precision and Confidence Plot. (d)-(f) Recall and Confidence Plot. (g)-(i) Precision and Recall Plot. (j)-(l) F1-Score and Confidence Plot. The first column is for the DiaMOS Plant dataset, the second column is for the Wheat Leaf dataset, and the third column is for the Rice Leaf Disease Dataset.

Table 6 Influence of Image Size on YOLOv5 Model.

Dataset	No. of Images	Image Size	GFLPOS	Training Time	mAP50
Wheat Leaf	407	640	47.9	0.384	0.819
Wheat Leaf	407	416	47.9	0.233	0.813
Rice Leaf Disease	120	640	47.9	0.171	0.872
Rice Leaf Disease	120	416	47.9	0.117	0.925
DiaMOS Plant	3007	640	47.9	2.754	0.894
DiaMOS Plant	3007	416	47.9	1.408	0.882



(a) Ground Truths



(b) Predictions

Fig. 10 Disease Detection by YOLOv5. Samples are from the DiaMOS Plant dataset.

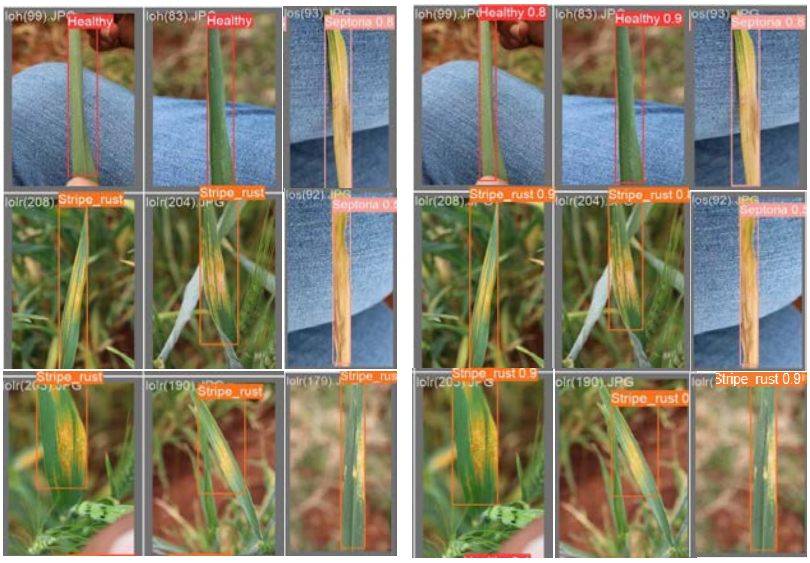
YOLOv5 misdiagnosed the diseases as in the first three columns of Fig. 11. The reason for this wrong prediction is mostly the position of the leaves, especially when the infected leaves are not on the front side, occluded by other leaves, placed at an angle, the resolution of the rear infected leaf is lower than the front infected leaf, there is uneven sunlight, or there is a presence of shadow. This happened due to the absence of such variations of data in the training dataset. If annotation is incomplete or not all the occurrence of instances in an image are not annotated, the training becomes partial. It increases FN and reduces *recall*. Fig. 12 shows some of the non-fully annotated data from DiaMOS Plant dataset. There were two cases when the model was able to detect all the instances, instead of incomplete annotation. The results are shown in the last two columns of Fig. 11. However, missing annotations represent poor data quality [28] which adversely affect the detection performance [83]. Hence, complete annotation will generate better performance of the model.

Fig. 11 Discrepancy from the ground truths for YOLOv5. Samples are from the DiaMOS Plant dataset. The top row shows the ground truths and the bottom row shows the predictions.

Fig. 12 Discrepancy in annotation in the DiaMOS Plant dataset. Yellow circles and ovals show the missing annotation.

Fig. 13(a) and 13(b) show the ground truths and the predicted values from the Wheat Leaf dataset. However, there are certain scenarios, as in Fig. 14, when there is discrepancy between the the predicted value and the ground truths. Not all instances have been detected or missed. As a result, FN is increased. This happened when the image is crowded with wheat leaves and leaves on the background are not focused.

Fig. 15(a) and 15(b) show the correctly and wrongly predicted results from the Rice Leaf Diseases dataset, respectively. The model shows a high confidence score for Bacteria_leaf_blight and Brown_spot. However, more data was necessary for Leaf_smut disease as the con-



(a) Ground Truths (b) Predictions

Fig. 13 Disease Detection by YOLOv5. Samples are from the Wheat Leaf dataset.

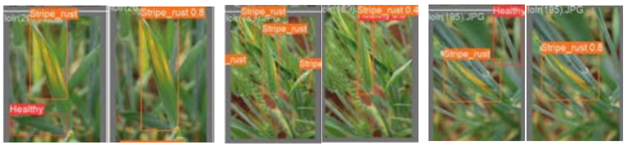


Fig. 14 Discrepancy from the ground truths for YOLOv5. Samples are from the Wheat Leaf dataset. Odd images (from left) are the ground truths and the even images are the predictions.

fidence score for the particular class is not so high. In some cases, Bacteria_leaf_blight and Brown_spot are wrongly predicted as Leaf_smut disease is generating higher false positives for Leaf_smut class.

(a) Correctly Detected Results. The top row shows the ground truths and the bottom row shows the predictions.

(b) Results for not correctly detected samples from Rice Leaf Disease dataset. The top row shows the ground truths and the bottom row shows the predictions.

Fig. 15 Disease Detection by YOLOv5. Samples are from the Rice Leaf Disease dataset.

5.2.2 YOLOv8

Fig. 16(a)-16(l) depict the performance metrics for YOLOv8. Metrics plots for the DiaMOS Plant dataset, the Wheat Leaf dataset, and the Rice Leaf Disease dataset are presented in the first, second, and third columns, respectively. Fig. 16(a)-16(c) depict plots of precision versus confidence. The plots of recall against confidence are displayed in Fig. 16(d)-16(f). Precision and recall plots can be seen in Fig. 16(g)- Fig. 16(i). The plots of f1-score versus confidence are displayed in Fig. 16(j)-16(l).

YOLOv8 achieved higher *precision* compared to YOLOv5 for DiaMOS Plant and Rice Leaf Disease datasets. Better *recall* than that of YOLOv5 has been achieved for Wheat Leaf and Rice Leaf Disease datasets too. However, we have achieved lower *recall* in YOLOv8 compared to YOLOv5 for DiaMOS Plant dataset. YOLOv8 excels in *f1-score*. In terms of *mAP50*, YOLOv8 and YOLOv5 perform similar for the DiaMOS Plant and Wheat Leaf datasets but YOLOv8 outperforms YOLOv5 for Rice Leaf Disease dataset. Image size was kept at 640×640 for both.

Fig. 17(b) and 17(a) show some sample predicted results by YOLOv8 and the corresponding ground truths from the DiaMOS Plant dataset.

There are some instances within the DiaMOS Plant dataset in which YOLOv8 did not perform as well as YOLOv5. The diseases were incorrectly diagnosed, as shown in Fig. 18. The reasons are the same as YOLOv5 and the main cause is not having a right image or due to some incomplete annotation in the dataset.

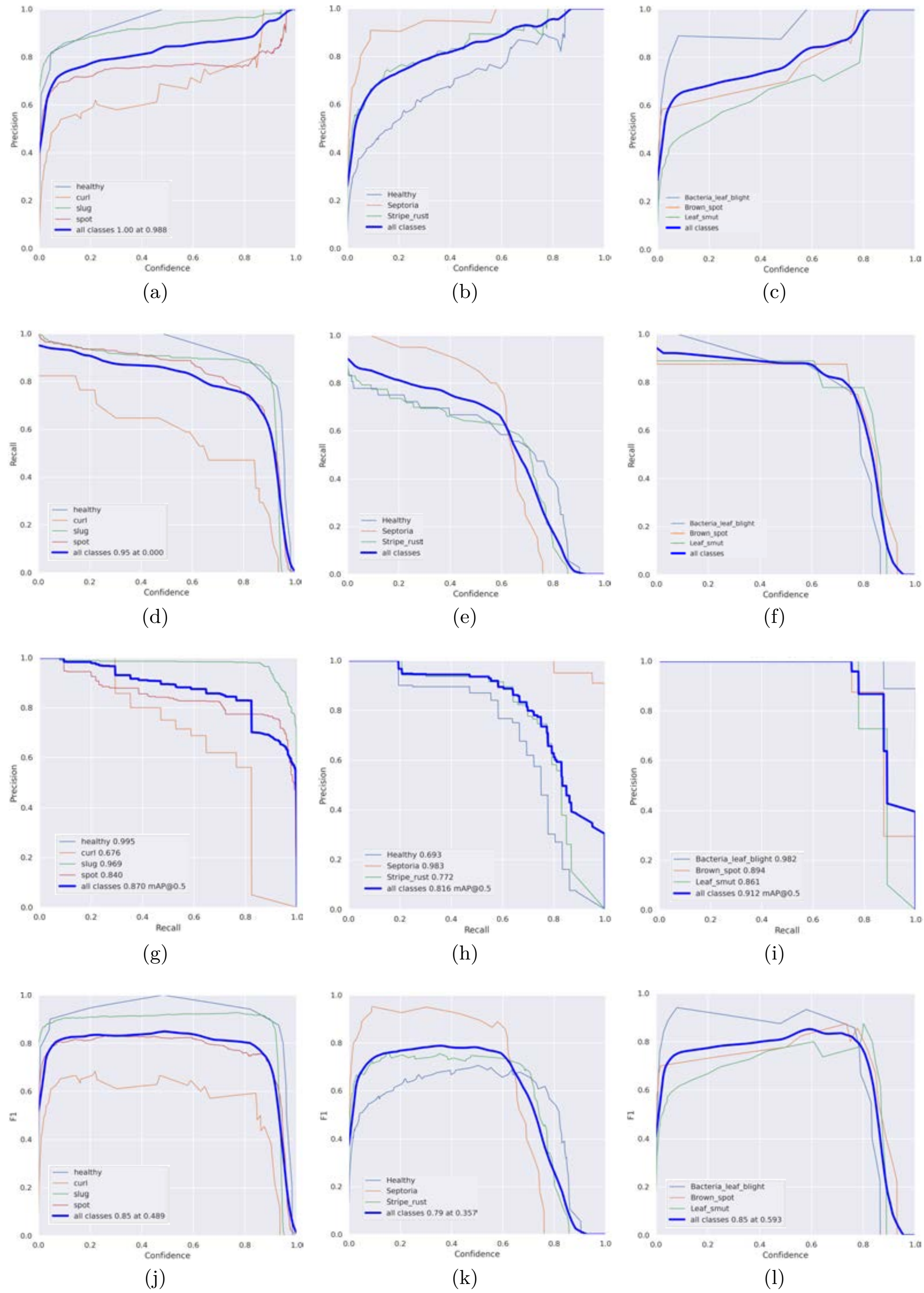


Fig. 16 Performance Metrics Plots of YOLOv8 for different datasets. (a)-(c) Precision and Confidence Plot. (d)-(f) Recall and Confidence Plot. (g)-(i) Precision and Recall Plot. (j)-(l) F1-Score and Confidence Plot. The first column is for the DiaMOS Plant dataset, the second column is for the Wheat Leaf dataset, and the third column is for the Rice Leaf Disease Dataset.

(a) Ground Truths (b) Predictions

Fig. 17 Disease Detection by YOLOv8. Samples are from the DiaMOS Plant dataset.

Fig. 18 Discrepancy from the ground truths for YOLOv8. Samples are from the DiaMOS Plant dataset. The top row shows the ground truths and the bottom row shows the predictions.

The ground truths and the predicted values taken from the Wheat Leaf dataset are displayed in the figures referred to as Fig. 19(a) and 19(b), respectively. Here, there are also some instances, such as the one shown in Fig. 20, in which there is a disparity between the predicted value and the ground truths which is expected for an image overcrowded with leaves.

Fig. 21(a) and 21(b) demonstrate the ground truths and the predicted values from the Rice Leaf Diseases with high confidence scores. Here also there are some cases when misdiagnosis happened, as in Fig. 22. Here also, there are FP cases of Leaf_smut disease.

Table 7 compares the performance metrics calculated for the two models for the three datasets. YOLOv8 performs similar to YOLOv5 for DiaMOS Plant and Wheat Leaf datasets but excels for Rice Leaf Disease dataset. So, YOLOv8 has finally been selected as the plant disease detector model. The performance metrics calculated for both networks show that the overall performance of YOLOv8 is better than YOLOv5. However, YOLOv8 took more time to train for the datasets used.

Table 8 compares the performance of "aGROdet 2.0," the plant disease detector, with existing works. Accuracy (ACC) and mean average precision (mAP) have been used to evaluate the performance of the various methods. "aGROdet 2.0" was able to achieve a high mAP even when field data was used, whereas the other works are totally based on the laboratory dataset.

Table 9 shows the inference times for the YOLOv8 model. It also states the pre- and post-processing times of the test image. When the symptom of a disease is not very clear or resembles other disease symptoms, the model takes longer time to detect. For simpler image or where the symptoms are clear, the model takes much a shorter time. As the inference time is in msec, if a video is used as the input instead of an image, a real-time detection of disease can be possible due to such fast inference process. This will be validated in future.

6 Conclusion and Future Work

Similar to all forms of life, plants are vulnerable to a wide range of diseases. Disease can prevent a plant from reaching its maximum growth potential [7,54]. It is well known that plant diseases are a leading cause of economic loss [55] due to harvest loss. All trees and plants must be free of any and all diseases. This is only possible when the disease is detected early which demands

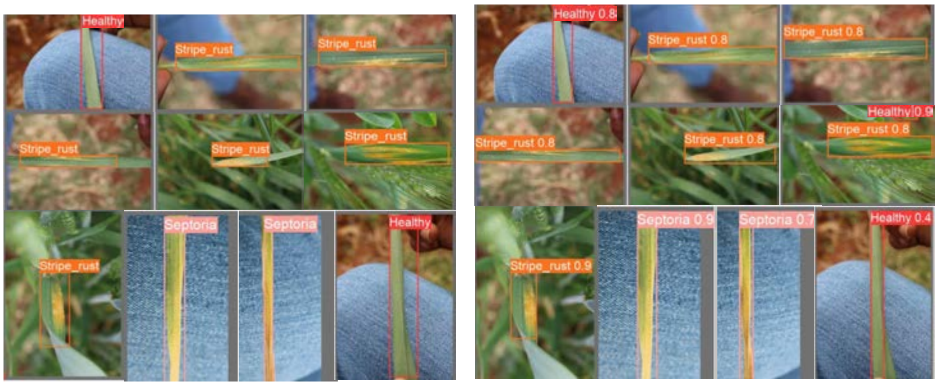
Table 7 Performance Metrics Comparison between YOLOv5 and YOLOv8.

Detection Network	**Dataset**	**Class**	**Precision**	**Recall**	**F1-Score**	**mAP**@50
YOLOv5	DiaMOS Plant	Healthy	1.000	0.964	0.870	0.995
		Curl	0.706	0.765	0.734	0.748
		Slug	0.949	0.905	0.926	0.976
		Spot	0.801	0.876	0.837	0.857
		Overall	**0.864**	**0.877**	**0.870**	**0.894**
YOLOv5	Wheat Leaf	Healthy	0.831	0.667	0.740	0.698
		Septoria	0.887	0.900	0.893	0.947
		Stripe_rust	0.809	0.679	0.770	0.812
		Overall	**0.869**	**0.749**	**0.796**	**0.819**
YOLOv5	Rice Leaf Diseases	Bacteria_leaf_blight	0.727	0.998	0.841	0.962
		Brown_spot	0.869	0.834	0.851	0.869
		Leaf_smut	0.640	0.778	0.700	0.783
		Overall	**0.745**	**0.870**	**0.805**	**0.872**
YOLOv8	DiaMOS Plant	Healthy	0.974	1.000	0.987	0.995
		Curl	0.851	0.706	0.772	0.767
		Slug	0.937	0.91	0.923	0.972
		Spot	0.752	0.843	0.795	0.839
		Overall	**0.879**	**0.865**	**0.872**	**0.893**
YOLOv8	Wheat Leaf	Healthy	0.658	0.694	0.676	0.693
		Septoria	0.949	0.933	0.941	0.983
		Stripe_rust	0.807	0.698	0.749	0.772
		Overall	**0.805**	**0.775**	**0.790**	**0.816**
YOLOv8	Rice Leaf Diseases	Bacteria_leaf_blight	1.000	0.869	0.930	0.982
		Brown_spot	0.795	0.875	0.833	0.894
		Leaf_smut	0.721	0.889	0.800	0.861
		Overall	**0.838**	**0.878**	**0.858**	**0.912**

Table 8 Comparative Analysis with the Existing Works

Papers	**Year**	**Plant Type**	**Method**	**Metric**	**Remarks**
Javidan et al. [38]	2023	Grape	SVM + K-means clustering + PCA	ACC=98.97%	Use of PlantVillage dataset makes the methods far from real life scenarios.
Morbekar et al. [57]	2020	Plants	YOLO	-	Use of PlantVillage dataset makes the methods far from real life scenarios.
Tial et al. [77]	2019	Apple	Improved YOLOv3	ACC=95.57%	Only one disease of a single plant has been detected.
Liu et al. [48]	2020	Tomato	Improved YOLOv3	ACC=92.39%	Tested with only one type of plant.
Mitra et al. [53]	2022	Apple	Mask R-CNN	mAP=83.8%	PlantVillage dataset has been used. No real field data has been tested.
aGROdet [54]	2022	Plants	Custom CNN + Pixel-based method	ACC=98.58%	PlantVillage dataset has been used. No real field data has been tested.
aGROdet 2.0 (Current Paper)	2023	**Plants**	**YOLOv8**	**mAP=**91.2%	**Real time and automatic detection of plant disease. Field data has been used.**

ACC → Accuracy; mAP → Mean Average Precision.



(a) Ground Truths (b) Predictions

Fig. 19 Disease Detection by YOLOv8. Samples are from the Wheat Leaf dataset.

Table 9 Inference Time for YOLOv8 Model for Each Dataset

Datasets	Time (ms)		
	Pre-process	**Inference**	**Post-process**
DiaMOS Plant	1.4	8.6	1.9
Wheat Leaf	0.2-1.7	11.1-14.2	0.8-1.2
Rice Leaf Disease	0.2	10.5-12.3	0.8-1.0

Fig. 20 Discrepancy from the ground truths for YOLOv8. Samples are from the Wheat Leaf dataset. The top row shows the ground truths and the bottom row shows the predictions.

(a) Ground Truths

(b) Predictions

Fig. 21 Disease Detection by YOLOv8. Samples are from the Rice Leaf Disease dataset.

Fig. 22 Not correctly detected samples of the Rice Leaf Disease Diseases dataset by YOLOv8. The top row shows the ground truths and the bottom row shows the predictions.

automatic and real time disease detection. In this paper, we have enhanced the work in [53] for automatic and real-time detection of plant diseases.

There are many ways this work can be enhanced further.

- More robust solution is needed for different lighting conditions, shadows, specular reflection, and the presence of insects.
- Some preliminary work on shadow removal has been done in [54] but more work is required in this area.
- Disease manifestations are different at different growth stages of plants. Datasets with such division is necessary.
- Data collection through smart phone camera is required to reflect the real world scenario.
- We hope that our work will help researchers pre-annotate new pear, rice, and wheat leaves infected with the addressed diseases and aid in the formation of a new dataset without much human effort.

Compliance with Ethical Standards

The authors declare that they have no conflict of interest and there was no human or animal testing or participation involved in this research. All data were obtained from public domain sources.

Acknowledgment

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