Designing an AI-Based Greenhouse Plant Monitoring System to Detect and Classify Plant Diseases from Leaf Images

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Plant diseases can significantly hinder food crop production, leading to substantial economic losses and posing a threat to global food security. Machine learning, particularly deep learning, plays a crucial role in object detection and classification. In this study, we present an AI-based plant monitoring system for detecting and classifying plant diseases using visual images. Our deep learning models are trained on plant images obtained from natural environments. Manual detection and classification are both challenging and labor-intensive, making accurate and timely diagnoses from an automatic system highly beneficial for treating plant diseases. Traditionally, plant disease detection using deep learning has relied on images taken in controlled environments, which do not support in-situ detection for remote monitoring. The Plantdoc dataset, a popular resource consisting of plant images from actual field conditions, is used in our study. We employ the YOLOv5 algorithm from the field of computer vision to the Plantdoc dataset, achieving results that surpass previous work on the same dataset. This success is attributed to our selected model and data augmentation techniques. Our model can classify and detect various diseased and healthy leaf classes with a mean Average Precision (mAP) of 92%. This capability enables farmers and researchers to remotely monitor plant health and diagnose plant diseases, thereby saving time, reducing costs, and minimizing crop loss.

Keywords. Machine Learning; Deep Learning; Artificial Intelligence; Plant Diseases and YOLOV5.

Introduction.

Plant diseases adversely affect agricultural productivity, causing significant damage to crops and impacting food production. According to the United Nations Food and Agriculture Organization (FAO), plants are key contributors to food security, with 80% of the human diet dependent on plants. Food production needs to increase by about 70% from current levels by 2050 to meet the food requirements of the growing world population. Plant diseases and pests are responsible for approximately 20% to 45% of global food production losses, amounting to over $220 billion annually, a substantial loss to economies and individual farmers [1]. For instance, in Sub-Saharan Africa, cassava mosaic disease (CMD) and cassava brown streak disease (CBSD) cause annual losses exceeding $1 billion [2]. Plant diseases can affect different parts of the plant, such as the root, stem, or leaf, with leaf diseases having the most significant impact on production [3,4]. Traditional methods of plant disease detection include visual inspection, fluorescence-based techniques, thermography, and hyperspectral imaging [5].

- **Fluorescence**. Utilizes DNA probes combined with microscopy to detect bacterial and pathogen infections in plants.
- **Thermography**. Uses thermographic cameras to detect infrared rays emitted from plant leaves, analyzing color differences to determine water loss caused by stomata damage from pathogens.
- **Hyperspectral imaging**. Employs hyperspectral cameras to collect data in three dimensions over wide geographical areas, analyzing reflectance resulting from biophysical and biochemical changes due to pathogens.

These traditional methods are time-consuming, expensive, and impractical for small farm holders [6]. An efficient, cost-effective solution for accurate automatic disease detection would benefit farming economies and enhance global food security. AI technologies, particularly machine learning (ML) and deep learning (DL), have shown robustness to variations in lighting conditions, plant poses, and types, offering a viable alternative.

Advancements in hardware and neural networks have accelerated the application of AI in various fields, including agriculture. AI-based systems leveraging computer vision have made significant progress in object detection and classification from visual images [7]. Research in the agriculture sector has explored automatic plant disease detection and classification systems using models [8] such as convolutional neural networks (CNN) [9], generative adversarial networks (GAN) [10], and hyperspectral methods [11]. These models have achieved success in extracting and identifying various types of crop information. Sophisticated and expensive equipment is often used for ground surveys or remote monitoring of crop health [12]. For example, the US forest health monitoring program collects data on forest ecosystems through meticulous manual observations and instrument recordings, followed by detailed analysis [13].

The agriculture sector employs chemical sprays, such as bactericides, fungicides, and nematicides, to control plant diseases. However, these sprays have side effects on the environment and plants, causing severe damage to the agroecosystem and incurring high costs. There is a need for more environmentally friendly and cost-effective methods for early plant disease detection to reduce the use of chemical sprays, ensuring less residual toxic chemicals on agricultural products, protecting groundwater from contamination, and minimizing environmental impact [13,31]. Early disease diagnosis with AI systems can reduce the need for chemical treatments and prevent disease spread.

Previous research on plant disease detection and classification using ML and DL models has relied on datasets such as PlantVillage, Digipathos, Northern Leaf Blight (NLB), and CD&S, which contain leaf images taken in controlled environments [14]. Results indicate that controlled or lab-based datasets are unsuitable for real-time plant disease detection and prediction. The PlantDoc dataset, introduced in 2020 by Davinder et al., consists of plant images captured in real environmental conditions [15]. Images with multiple leaves in background and different lightening condition are present. Their study achieved a mean average precision (mAP) of up to 39% using the Faster-RCNN-Inception-ResNet model after preliminary data processing and retaining only 27 classes with adequate representation.

We apply diverse data augmentation techniques to increase training data size and improve model generalization capabilities. Using the highly proficient You Only Look Once version 5 (YOLOv5) algorithm, [16] we developed an AI-based system for plant disease detection and classification. For the 27 classes, we achieved a mAP of 49% [15]. By balancing the dataset and removing underrepresented classes (retaining only 17 classes), we further improved the mAP to 92%. This enhanced system enables farmers and researchers to remotely monitor plant health, diagnose diseases early, and reduce crop loss and costs.

Literature Review.

Plant diseases can be detected using direct or indirect methods. Direct methods involve molecular-level analysis and require a large number of samples. Indirect methods include observing plants visually or examining their stress or volatility profile [17]. Common indirect methods are fluorescence, thermography, and hyperspectral imaging [5].

- **Thermography** detects variations in leaf temperature caused by infections from pathogens. Thermographic cameras capture color differences in leaves, indicating water loss due to stomata damage. However, this technique cannot identify specific diseases [17].
- **Fluorescence Imaging** detects chlorophyll fluorescence as a function of incident light on a leaf. This method is used to detect rust in wheat leaves by analyzing chlorophyll fluorescence variations at 470 nm [18].

In automatic plant disease detection, image processing techniques like image segmentation, clustering, and classification are used. The support vector machine (SVM) classifier has been utilized to detect and classify healthy and diseased plant leaves. Arivazhagan, Sai, et al. [19] used image segmentation and color co-occurrence as attributes to detect various diseases in 30 plants from around 500 images. Zhang, Shanwen, et al. [20] used the K-means clustering algorithm to segment diseased leaf images and separate healthy from diseased cucumber leaves using sparse representation.

Convolutional neural networks (CNN) have significantly advanced plant disease detection and classification. Kawasaki, Yusuke, et al. [21] proposed CNN-based methods for cucumber disease classification. Ferentinos [22] used different CNN algorithms like VGG, GoogLeNet, and AlexNet to classify various diseased and healthy leaf classes for 25 plant species. Another study used a deep convolutional neural network (Deep CNN) to classify 13 plant disease species from leaf images [23]. Durmuş et al. [24] deployed CNN algorithms AlexNet and SqueezeNet for tomato plant disease detection and classification, achieving successful deployment on Nvidia Jetson TX1.

Studies on the open-access PlantVillage dataset, consisting of images from 14 crop species and 26 diseases, used the DADCNN-5 architecture, achieving 99.93% accuracy on the test dataset and 97.33% accuracy on another dataset. The PlantDoc dataset has also been explored with a Siamese network for classification and detection [25]. Despite extensive research using machine learning and deep learning algorithms, deploying a practical and accurate system in the field remains challenging. Our literature review indicates the need for an automatic system for plant disease detection that is efficient and based on real environmental conditions for direct monitoring.

The YOLO algorithm, currently one of the most popular and efficient object detection and classification algorithms, is a single-stage neural network known for its speed and accuracy [26,30]. Singh, Davinder, et al. used the PlantDoc dataset and trained R-CNN and MobileNet models, achieving low accuracy [15]. We propose using the YOLOv5 algorithm, along with modifications to the dataset, to design a more accurate and efficient system for real-time plant disease detection.

Material and Methods.

The methodology of this research work consists of the following steps which are shown in figure 1.

Proposed Method.

The proposed method involves the implementation of YOLOv5 using Roboflow[27]. YOLOv5, pre-trained on the COCO dataset [28], is employed for its efficient object detection and classification capabilities. The PlantDoc dataset is uploaded and preprocessed using Roboflow, which ensures secure and confidential access to the dataset for training and testing.

Dataset Collection.

We utilize the PlantDoc dataset, originated by researchers at the Indian Institute of Technology and publicly available. According to the originators, this dataset closely mimics real field conditions, making it more representative than other available datasets [15]. The PlantDoc dataset contains 2,569 images with 8,851 labels, covering 13 plant species and 30 classes of diseased and healthy leaves. The classes include Apple Scab Leaf, Apple Leaf, Apple Rust Leaf, Bell Pepper Leaf Spot, Bell Pepper Leaf, Blueberry Leaf, Cherry Leaf, Corn Gray Leaf Spot, Corn Leaf Blight, Corn Rust Leaf, Peach Leaf, Potato Leaf Early Blight, Potato Leaf Late Blight, Potato Leaf, Raspberry Leaf, Soybean Leaf, Squash Powdery Mildew Leaf, Strawberry Leaf, Tomato Early Blight Leaf, Tomato Septoria Leaf Spot, Tomato Leaf Bacterial Spot, Tomato Leaf Late Blight, Tomato Leaf Mosaic Virus, Tomato Leaf Yellow Virus, Tomato Leaf, Tomato Mold Leaf, Tomato Two-Spotted Spider Mites Leaf, Grape Leaf Black Rot, and Grape Leaf. Some samples from the PlantDoc dataset are illustrated in Figure 2.

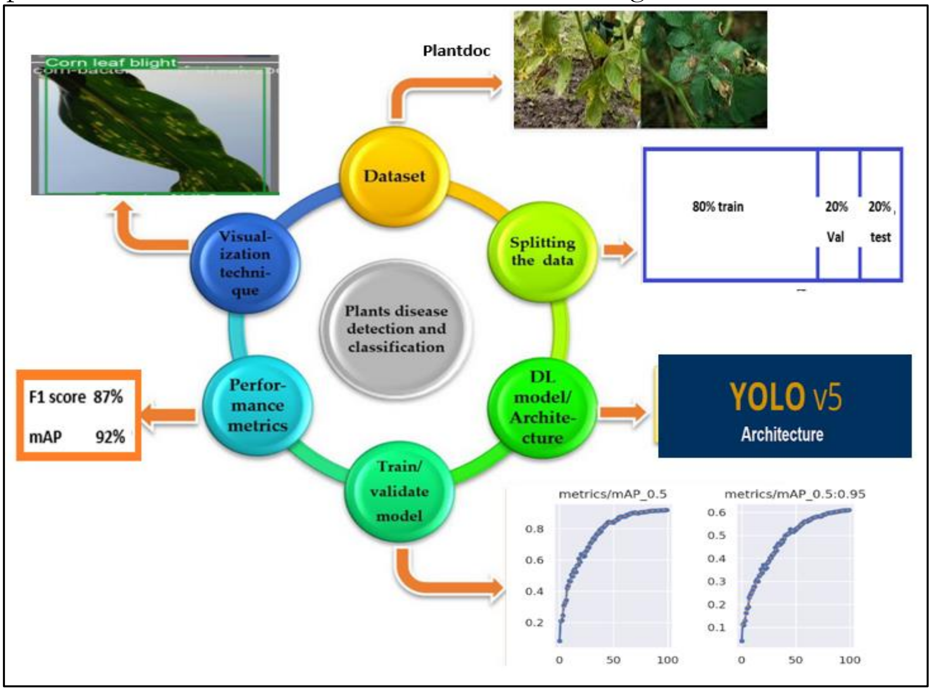


Figure 1. Steps of methodology.

Figure 2. Samples of plantdoc dataset.

Data Augmentation and Pre-Processing.

Upon analyzing the dataset, we observed a significant class imbalance, with some classes having too few images while others had a large number. To resolve this issue and enhance model performance, we employed data augmentation techniques. When the dataset was uploaded to Roboflow, it provided a detailed analysis of the dataset's health, including the exact number of classes and the number of images in each class. The results of this analysis by Roboflow [4] are shown in Figure 3.

We selected 17 classes from the total of 30 shown in Figure 3 and aimed to achieve class balance through data augmentation. The chosen classes are apple leaf, bell pepper leaf spot, bell pepper leaf, blueberry leaf, cherry leaf, corn leaf blight, peach leaf, potato leaf late blight, potato leaf, raspberry leaf, soybean leaf, squash powdery mildew leaf, strawberry leaf, tomato Septoria leaf spot, tomato leaf bacterial spot, tomato leaf late blight, tomato leaf mosaic virus, tomato leaf yellow virus, and tomato mold leaf.

We applied a range of augmentation techniques to the dataset, including horizontal flips, 90° clockwise and counter-clockwise rotations, rotations of -15° and +15°, shear transformations of ±15° horizontally and vertically, and adjustments in saturation and brightness ranging from ±25%. Additionally, we introduced blurring up to 2.5 pixels and noise up to 5% of pixels. These augmentation processes were implemented using Roboflow. As a result, the total number of images increased to 12,990. Figure 4 illustrates some of the samples from the PlantDoc dataset after applying these augmentation steps. Furthermore, the dataset's health improved, as depicted in Figure 5, following the augmentation procedures.

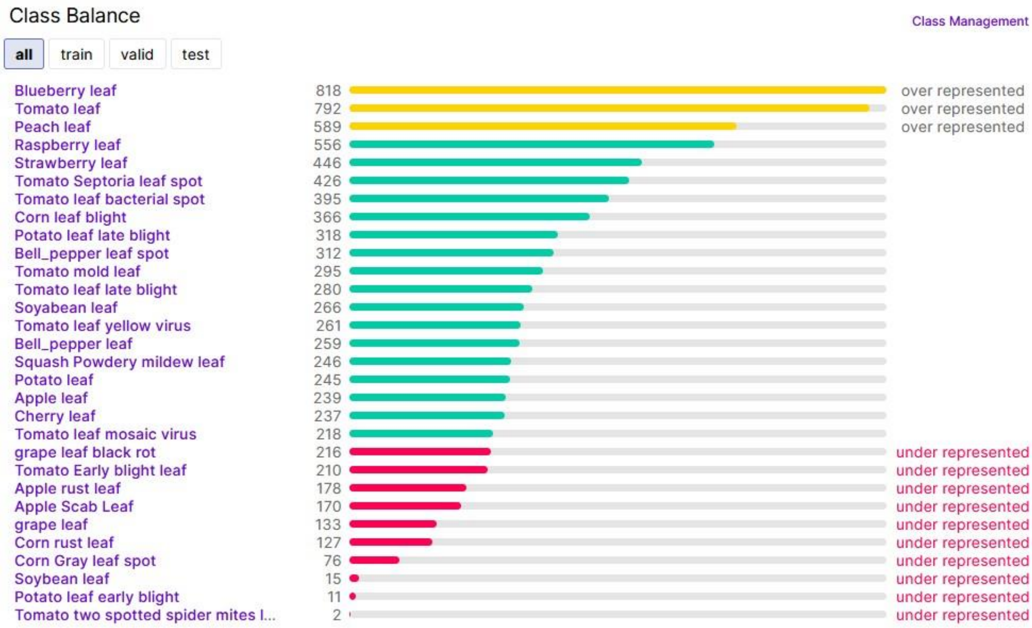


Figure 3. Original plantdoc dataset health, images in each class and total classes shown by Roboflow.

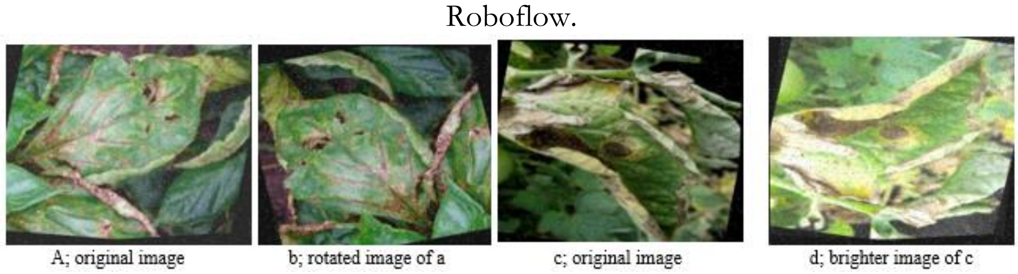


Figure 4. Samples after augmentation applied.

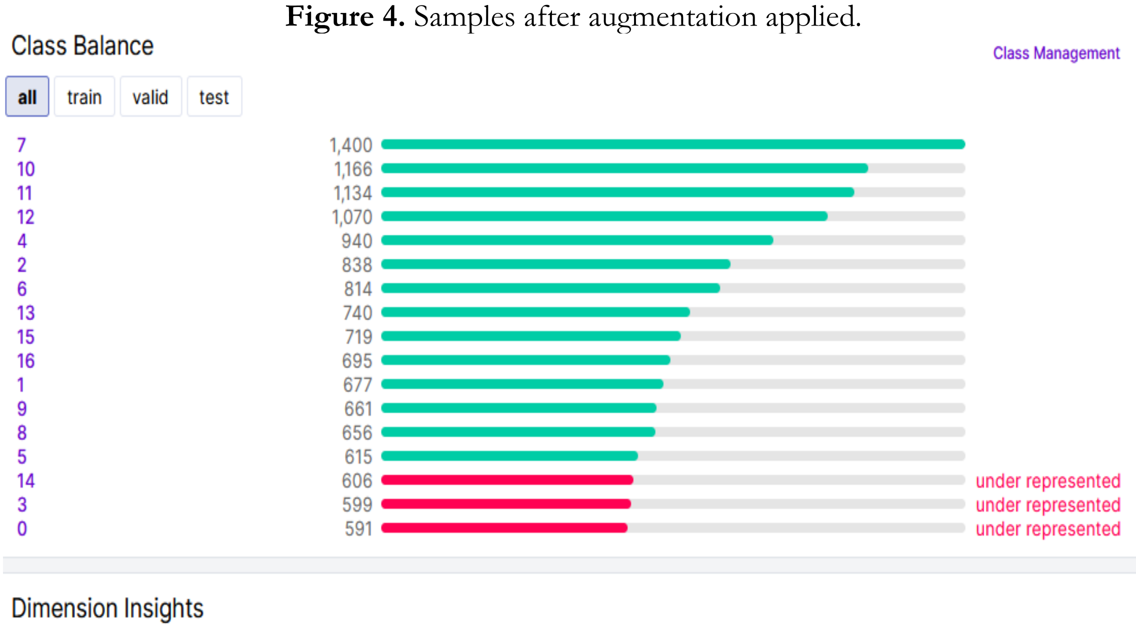


Figure 5. Improved dataset health after augmentation applied.

For model training and testing, we utilized Google Colab, benefiting from its free access to powerful GPUs. We are grateful to Google Colab for this resource. The training process spanned 100 epochs, taking a total of 3 hours and 20 minutes to complete. The YOLOv5 algorithm consists of three main components. the head, neck, and backbone. Figure 5 displays the full architecture of YOLOv5, as provided by Ultralytics.

Backbone.

The YOLOv5 algorithm employs the CSP (Cross-Stage Partial Networks) backbone, a convolutional neural network that extracts image features at various granular levels. The backbone incorporates the BottleNeckCSP [29], which enriches the feature extraction process and reduces gradient duplication during CNN optimization. Additionally, the SPP (Spatial

Pyramid Pooling) module is integrated to expand the receptive field of the network, enhancing its ability to capture spatial hierarchies [29].

Neck.

The neck of YOLOv5 comprises several network layers that aggregate and refine image features before passing them to the prediction layer. Feature pyramids are created through these layers, aiding the model in generalizing across different object scales. YOLOv5 utilizes PANet [5] for this purpose, generating feature pyramids that improve the model's performance on a range of object sizes and scales.

Head.

The head of the network is responsible for predicting bounding boxes, classifying objects, and identifying image features. YOLOv5 operates on a regression-based approach with a streamlined pipeline, enabling high-speed processing. It can handle real-time video streams with a latency of less than 25 seconds. During training, YOLOv5 focuses on global context within the target regions, aiming to classify objects and predict bounding boxes directly from the entire input image.

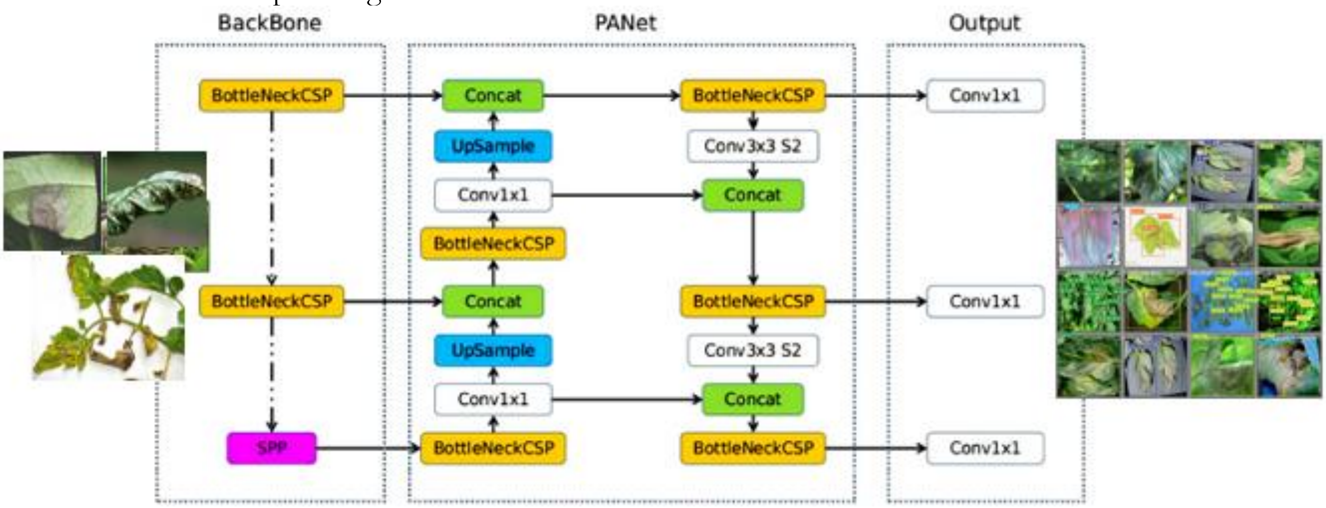


Figure 6. Architecture of YOLOv5 model.

Results and Discussion.

Our results, obtained using the YOLOv5 small model, demonstrate significant improvement over those reported by Davinder et al. [15]. These enhancements stem from dataset modifications, including data augmentation and class balancing. Table 1 displays the performance metrics of YOLOv5 on the original PlantDoc dataset. In contrast, Table 2 presents results from the augmented and balanced dataset, showing substantial improvements. Specifically, our model achieved a mean Average Precision (mAP) of 92.0%, surpassing the 38.9% mAP reported by Davinder et al. [6]. This improvement underscores the effectiveness of our data processing techniques and YOLOv5's capabilities in plant disease detection.

Table 1. Results based on original plantdoc dataset.

Model	Pre Trained Weights	mAP@50%
YOLOv5	COCO	49.7

Table 2. Comparison of results with existing work.

Model, Use By	Pre Trained Weights	mAP@50%
MobileNet, Davinder, et al.	COCO	32.8
MobileNet, Davinder, et al.	COCO+PVD	22.4
Faster rcnn inception resnet, Davinder, et al.	iNaturalist	36.1
Faster rcnn inception resnet, Davinder, et al.	COCO	38.9
YOLOv5, our model	COCO	92.0

The YOLOv5 model significantly enhances the detection of both small and large disorders. Key performance metrics, including mean Average Precision (mAP), precision, recall, and F1 score, show notable improvement, particularly when using a balanced dataset. The F1 score, which ranges from 0 to 1, is a measure of a model's accuracy that balances precision and recall. A score of 0 indicates no accuracy or recall, while a score of 1 signifies perfect accuracy and recall. Similarly, mAP is calculated by averaging the Average Precision (AP) across all classes, providing a comprehensive assessment of the model's overall performance [5].

Figure 7 presents the confusion matrix of the model, a critical tool for assessing its performance. The confusion matrix provides a clear view of the model's predictive accuracy by showing the relationships between actual and predicted classes. It includes key metrics such as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), which are essential for calculating accuracy, recall, precision, and specificity.

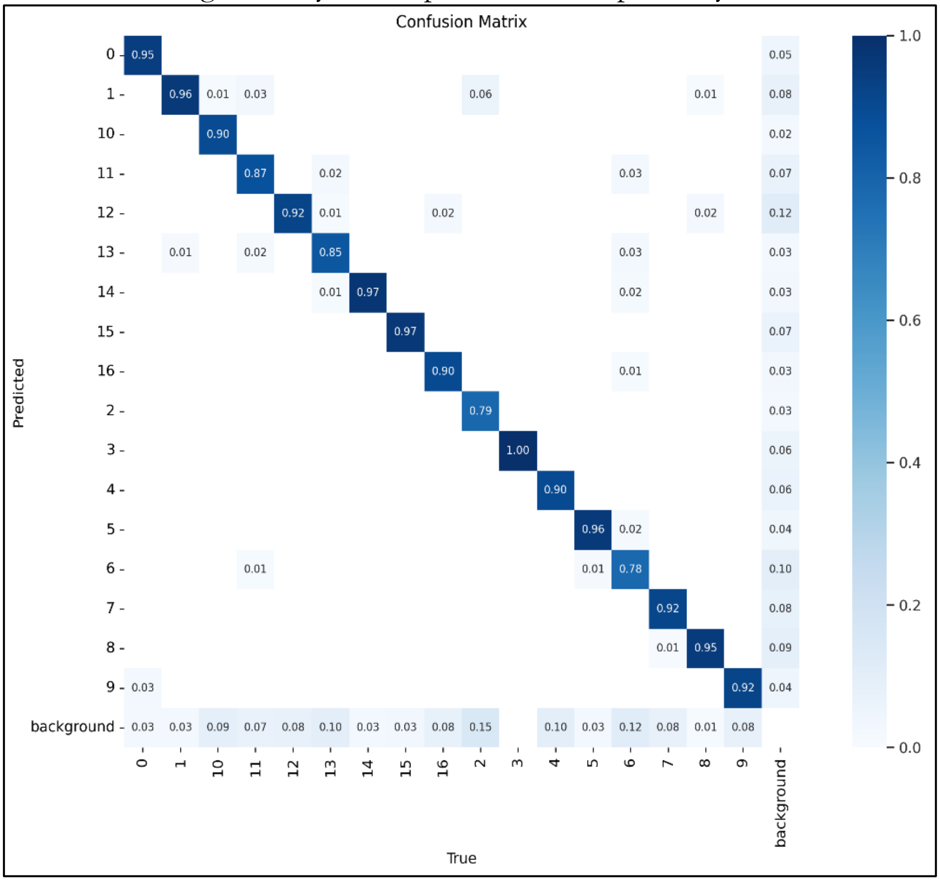
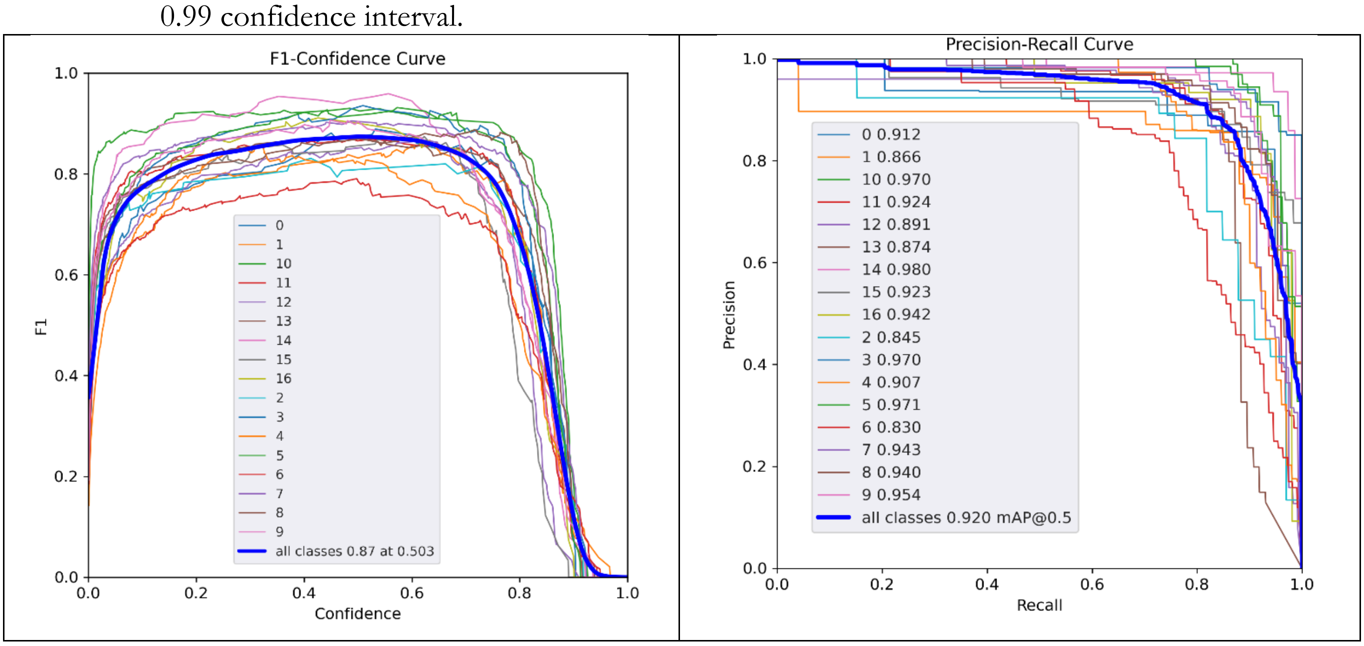


Figure 7. Confusion matrix.

The F1 score, a weighted harmonic mean of precision (P) and recall (R), is used to evaluate the model's balance between these two metrics. An F1 score of 0.87 is achieved with a confidence value of 0.503, indicating optimized recall and precision. As shown in Figure 8, both confidence and F1 score are ideally maximized. The accuracy is represented by the confidence interval, which helps define the effect magnitude. Larger sample sizes improve estimate precision. The confidence interval, with a range of 0.935, reflects a precision level of 1.00. A larger sample size leads to more accurate estimates, and the confidence interval indicates the recall with which the effect magnitude is recorded. Practically, sample size significantly impacts recall accuracy. The recall value and confidence interval together provide a comprehensive understanding, as depicted in Figure 8, where a recall value of 0.00 falls within the effects of a 0.99 confidence interval.



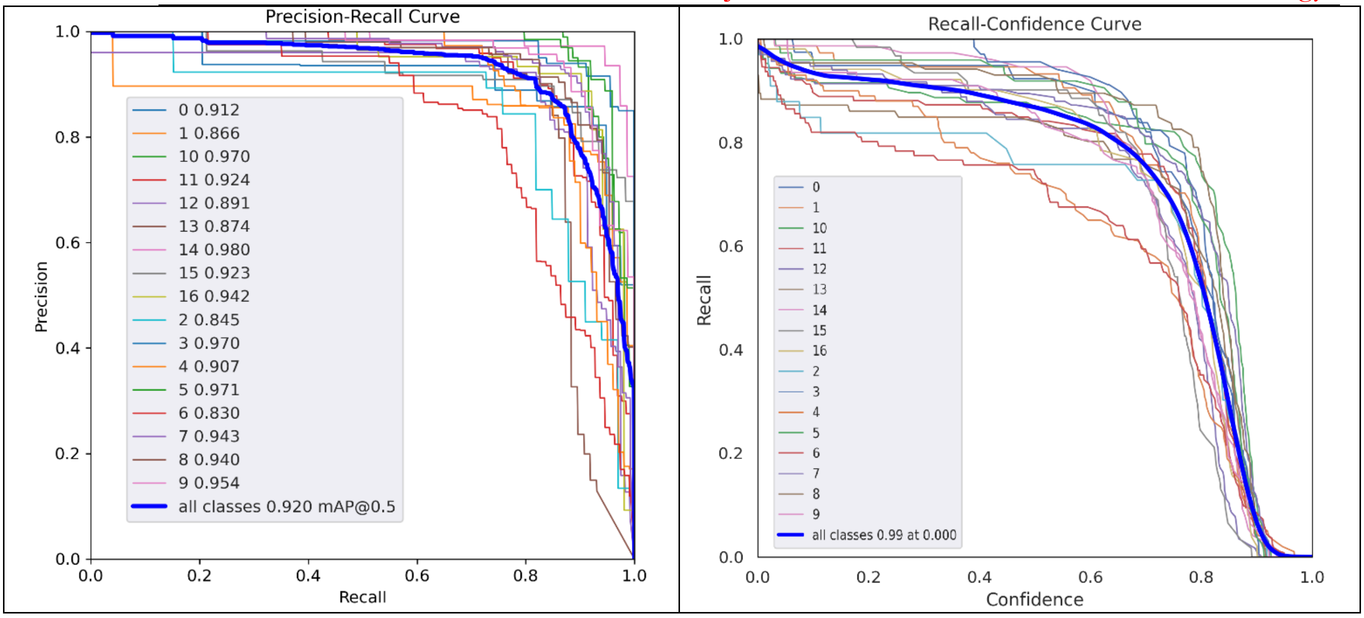


Figure 8. Recall-confidence, Precision-recall, F1 and Precision-confidence curves.

The precision and recall curve shown in Figure 8 illustrates the tradeoff between precision and recall across various thresholds. A high area under the curve signifies both high precision and recall. High precision is associated with a low false positive rate, while high recall is linked to a low false negative rate. As indicated in Table 2 and Figure 8, we achieved a Mean Average Precision (mAP) of 0.920. The model was trained for 100 epochs using both the training and validation sets. During this process, we tracked the detection frame loss, detection object loss, and classification loss for both sets, as shown in Figure 9. The dataset included 11,930 training and validation images, with 450 images reserved for testing. The improvements in model performance are attributed to the modifications and augmentations applied to the dataset.

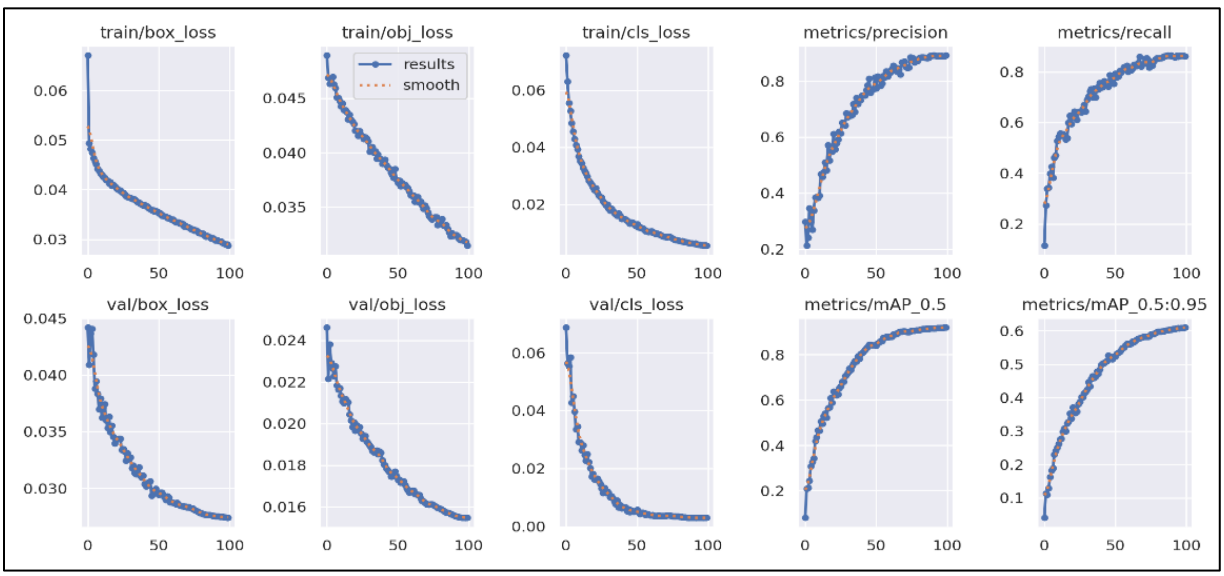


Figure 9. Loss graph of the dataset.

Conclusion.

Plant disease detection is crucial for timely treatment, which helps enhance the production and quality of agricultural products. This article demonstrates significant improvements in plant disease detection by leveraging the state-of-the-art object detection model, YOLOv5. YOLOv5 outperforms other CNN models such as SVM, VGG, GoogLeNet, and AlexNet in terms of accuracy. Using the PlantDoc dataset, which was augmented to include 12,990 images, the YOLOv5 small model achieved benchmark results with an accuracy of 92.0%, as shown in Table 2. This represents a substantial improvement over existing models.

This paper focuses on developing an advanced plant disease detection system based on YOLOv5 and a dataset reflecting real field conditions. Although YOLOv5 has been employed in various research studies for object detection and classification, further refinements are needed to address the complexities of diverse plant species and environmental backgrounds. Future work will aim to optimize YOLOv5 models for faster and more accurate detection in increasingly complex scenarios.

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Author's Contribution.

- 1st **Author.** Author has collected data and run the experimentation and data augmentation and preprocessing and obtaining result and writing all the work.
- 2nd **Author.** Supervises all the methodology and research work and guidance.
- 3rd **Author.** Proof reading and mistakes correction in the research writings and guidance.

Conflict of Interest. We no conflict of interest for publishing this manuscript in IJIST.

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