Real-Time Plant Disease Detection using YOLOv5 and Live Camera Integration

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***Abstract*—One of the most significant aspects of agricultural productivity is plant diseases, which tend to incur considerable losses in case the disease symptoms are not determined in time. In this regard, this paper suggests a real-time system of plant disease identification with the help of deep learning, computer vision, and cloud implementation. In this respect, the proposed system will be facilitated by the YOLOv5 object detector model to identify the various plant leaf illnesses in real time picture streams with precision. This is first implemented on a local machine with the use of OpenCV-based integration with the webcam to perform real-time testing of the accuracy of the detection, the quality of the bounding box, and the speed of the inference on sample leaves. Having reached the stable results in a controlled environment, the system will be implemented on an AWS EC2 cloud server so that it could be accessed remotely and interlinked with other external cameras devices such as Raspberry Pi modules and IP cameras placed at agricultural fields. This architecture will facilitate sustained surveillance, real time disease detection, and production of alerts to be taken by the farmers to ensure there is no harm in the crop. The article offers a scalable, practical, and socially meaningful proposal to precision farming that employs the deep learning and IoT-equipped camera systems to detect the emerging disease in the agricultural field.**

***Index Terms*— YOLOv5, Deep Learning, Real-Time Object Detection, Computer Vision, OpenCV, AWS EC2, Cloud Deployment, Raspberry Pi Camera, Precision Agriculture, Live Camera Integration, Agricultural Automation, Image Processing, Smart Farming.**

I. INTRODUCTION

Plant diseases constantly threaten agriculture as it is the source of food to the world, and any moment, the yield and quality of the crop will decrease. Detection of plant diseases has become very vital in ensuring that there is minimal loss in the economy, less transmission of diseases and promotion of sustainable agriculture. Conventional methods of disease detection are extremely dependent on human eye inspection of farmers or specialists. It is typically tedious, subjective and may be full of human errors in mass farming conditions where continuous monitoring may be difficult. Thus, an automated, precise plant disease detection system in real-time, capable of operating in the conditions of a real-world factory, is keenly anticipated.Recent advances of AI, in particular, the deep learning-based computer vision have brought impressive transformations to the field of automated disease detection. Among them, object detection models such as YOLO are essentially performing remarkably well, as far as the detection of diseases and their location within an image are concerned. YOLOv5 is among them and can provide a good balance between low accuracy and high inference speed, as well as a lightweight architecture that may be potentially applied to real-time applications. These features ensure it would be a great option in plant disease detection, where the quick processing regime and instant feedback is crucial. Nevertheless, the majority of the literature reports are concerned mostly with the classification of disease on a case-by-case basis on the basis of static images elicited on controlled datasets. Though such studies can be useful, they cannot satisfy the actual environmental challenges that are in agriculture because they are likely to be influenced by lighting conditions, leaf orientation, background clutter, and environmental variability on the detection performances. Real-time monitoring usually involves the need to be combined with live camera systems and scalable deployment options-where the traditional statical style of images fails to perform. To address this shortcomings, this study will suggest a real-time plant disease detection system that combines YOLOv5 with live camera feeds to monitor the plant health in real-time. It is initially trained and tested on a local environment through OpenCV based webcam integration to, therefore, allow real-time visualization of bounding boxes, frame by frame disease detection, and performance evaluation under controlled environment. This step makes models reliable, faster in inference and makes sure that detection accuracy is correct before the model can be deployed to the field.

II. LITERATURE SURVEY

Following the development of deep learning, in particular, convolutional neural networks (CNNs), the focus of research on plant disease detection now turned towards automatic feature extraction on large labeled datasets. The initial research showed that CNNs, including AlexNet, VGG, ResNet, and Inception, could learn discriminative visual representations using direct access to raw leaf images that greatly surpassed the traditional image processing methods. Mohanty et al. demonstrated that deep CNN models that were trained on the PlantVillage dataset were capable of very high classification accuracy on a variety of crop diseases, which demonstrates the effectiveness of deep learning in plant health evaluation [1]. Likewise, Ferentinos compared the results of multiple CNN architectures and ensured that deep learning models can offer strong disease detection when the images are taken under controlled conditions [2].

Although they have shown good performance, CNN-based classification methods can only perform the analysis of static images and they do not offer localization of diseased areas. In addition, these methods can usually presuppose controlled backgrounds and equal light conditions which limit its use in natural agricultural settings. In order to counter these shortcomings, recent studies have paid attention to object detection methods which allow localizing and classifying plant diseases at the same time. More specific attention has been paid to single-stage detectors based on the YOLO because of their high inference speed and ability to be deployed in real-time. Zhao et al. have shown that a better YOLOv5 model will be capable of detecting crop diseases with better localization performance and also retain real-time processing power [9]. In the same manner, Zhu et al. suggested a lightweight platform advertised as YOLOv5-based and implemented to identify the presence of apple leaf disease and obtained a desirable tradeoff in accuracy and computational efficiency [5].

In addition to model architecture, robustness and generalization are also important issues in real-world deployments. Cap et al. solved this problem by proposing a hard-sample re-mining approach which enhances performance in detecting with problematic conditions of occlusion and background clutter [7]. Model hierarchical detection frameworks have also been investigated that can be used to aid viable diagnosis in complex agricultural environments. The hierarchical object detecting method suggested by Iwanie et al. uses the method of multi-stage inference to increase the accuracy of recognizing the disease through this approach [8]. All these studies show that the YOLO-based object detection models are suitable in real-time monitoring of plant diseases.

Along with the improvement of the algorithms, cloud computing and IoT technologies have also contributed to the development of the smarter farming system. Nyakuri et al. and Akbar et al. surveys underscore the fact that scalable, remote, and continual monitoring of agriculture can be effected taking into consideration the integration of deep learning and IoT-enabled sensing and cloud platforms [3], [4]. There is a possibility of video streams being processed in real-time with cameras installed in the field and the decision-making process taking place based on the centralized analytics which is possible via cloud-based deployment. Nevertheless, most of the currently existing systems are based on offline analysis of images or do not offer real-time object detection functions.

According to the literature available, a scalable, real-time plant disease detection system, combining the object detection of the YOLOv5 algorithm with live camera feeds and the deployment on the cloud is still not present. The given work fills it by integrating real-time YOLOv5 inference and live video streams with cloud-executed code running on AWS EC 2, which allows monitoring disease dynamics in real-life agricultural conditions in a convenient and active way.

III. Methodology

Detect the pipeline, including dataset preparation, based on YOLOv5, training of models, real time inference on the web camera, and deployment in the AWS EC2. In this research methodology, the investigator will introduce a systematic way of designing, developing, and assessing a live plant disease detector system based on the YOLOv5 deep learning framework with real-time camera streams. The workflow is going to be broken down into multiple sections: dataset preparation, training of the model, the local real- time detection with the use of the OpenCV, and the remote monitoring with the help of the cloud deployment on the AWS EC2. It is to be done in every step to make sure that the solution proposed is correct, scalable and can work in the actual agricultural settings. This initial step of the approach is associated with the gathering of data and its pre-processing. The datasets such as the PlantVillage, among others, are publicly available, and field images are also taken by the authors themselves to make sure that there is variety in the disease patterns, in the lighting conditions, and the background of the leaves. To make the model more robust, images are collected, preprocessed by means of resizing, normalization, and augmentation, such as flipping, rotation, adjusting brightness, and changing contrast. Labeling is performed by the use of annotation software, like LabelImg, with bounding boxes being drawn around tissue disease locations. They are then transformed to YOLO format which contains the name of the class and normalized coordinates of each bounding box.

The other phase is concerned with real-time tracked with the help of local web-cam that is built-in with OpenCV. To this end, a real-time detection script has been written to capturing frames constantly of the webcam and inputting them into the YOLOv5 model, bounding boxes, and disease notice labels as superimposed on recognized areas. At this phase, the frame rate, inference time per frame and the rate of detection is obtained to ensure that the system can work in real-time.

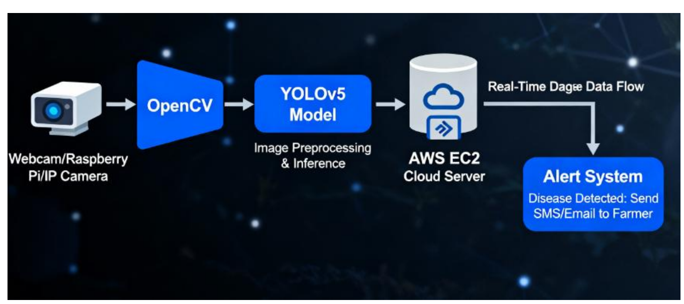


Fig. 1. System Architecture

Fig. 1 represents the general plan of the proposed real-time plant disease detection system, which focuses on the combination of live camera feed, inference using YOLOv5, and deployment on the AWS EC2 remote monitoring. Webcams, Raspberry Pi, or IP cameras may be utilized on the device layer to capture images in a flexible way in an experimental setting and in the real-life farming conditions. Its open CV implementation, through which frames are captured on a local machine and then sent to the cloud, eliminates the need to do extensive computation on the on-board device, which nonetheless allows near real-time processing. The design is compliant with the edge-cloud paradigms in precision agriculture, in which tiny devices can perform sensing and communication, and servers can conduct deep learning inferences.

A. Network Architecture of YOLOv5-ENDoculo.

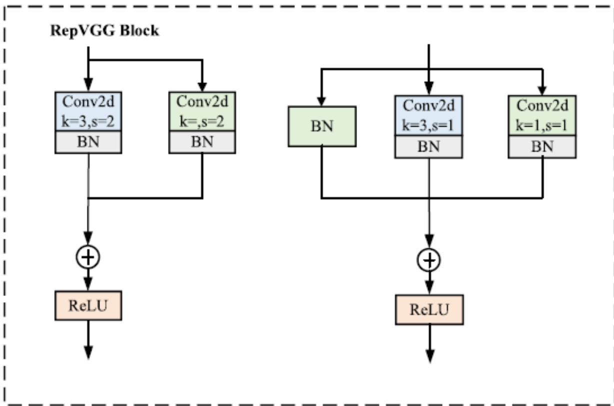


Fig. 2. Network Architecture of YOLOv5-EFFICIENT

Fig. 2 illustrates the internal structure of the YOLOv5 model that is utilized in this work. It is designed using the single-stage object detection paradigm where features are obtained using CSPNet and aggregated using ELAN as applied in recent object detection paradigms [9], [11].

The enhanced model of YOLO V5 is known as YOLO V5- EFFICIENT. According to the concept of feature fusion of CSPNet and the concept of integrating residual structures, the RepVGG Block is recommended to replace the BottleNeck Block of YOLO V5 as the main branch of gradient flows. The RepVGG Block is further enhanced by introducing the concepts of Efficient Layer Aggregation Network (ELAN) to make it lightweight, yet receive superior gradient flow information. The CBAM is incorporated to improve the network to extract the information on features. The addition works to enhance the network representation of the lesion features and deactivate interference of irrelevant information. Particularly optimized network structure is drawn in the fig.2.

Therefore, the general mathematical model is a whole system converting raw image frames into bounding box predictions and probabilities of disease classification by convolutional process, regression, probabilistic scoring, and optimization methods. The mathematical model is the core of the YOLOv5-based real-time plant disease-detecting pipeline that was used in this study. The regression of the bounding box, estimation of the confidence and the non-bounding box. maximum suppression steps are built on the top of the normal YOLO detecting. framework described in [9], [11].

B. Mathematical Modelling

The mathematical simulation of the proposed real-time plant disease detector system is founded on the principles of feature extraction and bounding box regression, along with object detection and classification probability estimation as the implementations in the YOLOv5 architecture. A combination of image representation, convolution operations, confidence scoring, and Non-Maximum Suppression (NMS) may be used to describe the model, where diseased areas are detected using input of a live camera. An image receiving is an input frame given by the webcam or remote camera:

$$I \in \mathbb{R}^{\{H \times W \times 3\}}$$

where His the height, and Wis the width and the three channels, are the three color intensities of RGB. YOLOv5 contains this image in a grid of SxScells. Every cell of the grid is a prediction of the bounding box and a confidence score. Given each prediction of a bounding box B i, the model approximates parameters.

$$B_i = (x_i, y_i, w_i, h_i)$$

with (xi,yi) indicating the location of the center of the bounding box, and (wi,h i) indicating its width and height all with respect to the image dimensions. The score of confidence of each bounding box is determined as:

$$C_i = P(object) \times IoU\left(B_i, B_i^{\{gt\}}\right)$$

Thus, the overall mathematical model represents a complete system that transforms raw image frames into bounding box predictions and disease classification probabilities through convolutional processing, regression, probabilistic scoring, and optimization techniques. This mathematical formulation forms the foundation of the YOLOv5-based real-time plant disease detection pipeline employed in this research.

The bounding box regression, confidence estimation, and non- maximum suppression steps follow the standard YOLO detection framework described in [9], [11].

C. Performance Evaluation

The performance analysis is quite a significant step of ensuring the reliability, precision, and timeliness of the presented YOLOv5-based plant disease detection system. After the training stage of the model, there are a series of both quantitative and qualitative tests that are carried out to measure the performance of the model on both unknown data and live video-stream. The trained model is initially tested using a special test set which contains plant leaf images that are not utilized in the training and/or validation. The testing stage assists in the determination of the generalization capacity of the model and its tolerance to the new changes in the color, shape, light and the disease intensity of leaves. These are precision, recall, F1-score, and mean Average Precision of various IoU thresholds, i.e. mAP.5 and mAP.95. Precision The correctness with which the model labels the identified bounding boxes, and recall A measure of the ability of the model to detect all the instances of diseased leaves existing within the image.

Metric	Description
Precision	Measures the correctness of detected diseased leaf regions.
Recall	Evaluates the model's ability to detect all diseased instances.
F1-Score	Provides a balanced measure of precision and recall.
mAP@0.5	Indicates overall detection accuracy at 0.5 IoU threshold.
mAP@0.5:0.95	Evaluates detection performance across multiple IoU levels.
IoU	Measures overlap between predicted and ground-truth bounding boxes.
FPS	Determines real-time processing speed of the system.
Latency	Measures time taken to process each video frame.

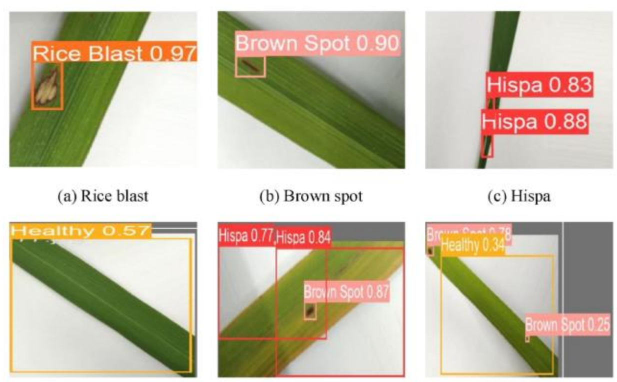
TABLE I: PERFORMANCE EVALUATION METRICS

Table 1 summarizes the evaluation metrics used to assess the performance of the proposed system. These metrics are commonly used in object detection tasks to measure accuracy, localization quality, and real-time performance [11]. The F1-score provides the balanced between the accuracy and recall. MAP is regarded as the primary measure of performance, as this metric reveals the quality of the entire object detection mechanism of the model in terms of accuracy-recall curves in all classes. Thus, the increased values will mean the improved consistency of the performance of the detection concerning various types of diseases. In order to examine the patterns of errors in the model, the confusion matrix is drawn up to see the misclassifications in the classes. This will indicate what diseases the model can often confuse with others and therefore possibly allow some form of improvement like refining of the datasets or hyperparameter optimization.

IV. RESULTS AND ANALYSIS

Besides testing of static images, the system was made to work with the OpenCV based real-time live testing on the web camera to test the performance of real-time detection. The model was capable of keeping the rate of inference constant, and with a GPU-enabled setup it could smoothly detect 20-30 FPS and with a CPU-only system it detected at 8-15 FPS based on hardware capacity. This, therefore, affirms that the system can detect in real-time and not suffer any apparent lag. Bounding boxes were successful with respect to leaf regions and confidence scores did not decrease among successive frames indicating high temporal consistency. Good performance occurred under the following variation factors; mild motions of the leaf, partial occlusion and variation in distance between the camera and target object, however, extreme low-light conditions marginally decreased the confidence in the detection of those objects. The qualitative findings further indicated that the model can be readily generalized beyond a test in the laboratory: when tested on field-captured images and live leaf samples, the detection was reliable, which suggests that augmentation and transfer learning employed in the process of training was effective.

The visual outputs had distinct bounding boxes and class identities that were easy to interpret the disease to the user. The tests on the cloud deployment were performed with the help of AWS EC2; in the course of the tests, the model maintained consistent inference times, which proved its scalability to remote agricultural tasks when a large number of camera streams are handled at the same time. All of these findings prove that the suggested plant disease detection system using YOLOv5 can support high accuracy, low latency, and high real-time performance, which is appropriate to be incorporated into smart farming systems. This model has the capacity to harmonize its strength in detecting with high accuracy and low real-time inference, which makes it feasible and effective in the initial detection of plant diseases in an agrarian setting.



(a) Rice blast (b) Brown spot (c) Hispa

(d)Healthy (e) Brown spot and hispa (f) Brown spot and healthy

Fig. 3. Disease Detection

Fig. 3 illustrates the qualitative detection capability of the proposed YOLOv5-based system under different plant health conditions. The model accurately localizes and classifies individual disease regions such as rice blast, brown spot, and hispa with high confidence scores, as shown in Fig. 3(a)–(c). Fig. 3(d) demonstrates correct identification of a healthy leaf without false disease predictions, indicating good class discrimination. In more complex scenarios where multiple disease types coexist on a single leaf, as shown in Fig. 3(e), the system successfully detects and distinguishes overlapping disease instances, highlighting its multi-class and multi-instance detection capability. Fig. 3(f) further shows the model's robustness in identifying both diseased and healthy regions within the same frame. These qualitative results confirm the effectiveness of the proposed approach in handling real-world agricultural conditions involving background variation, overlapping lesions, and mixed disease patterns.

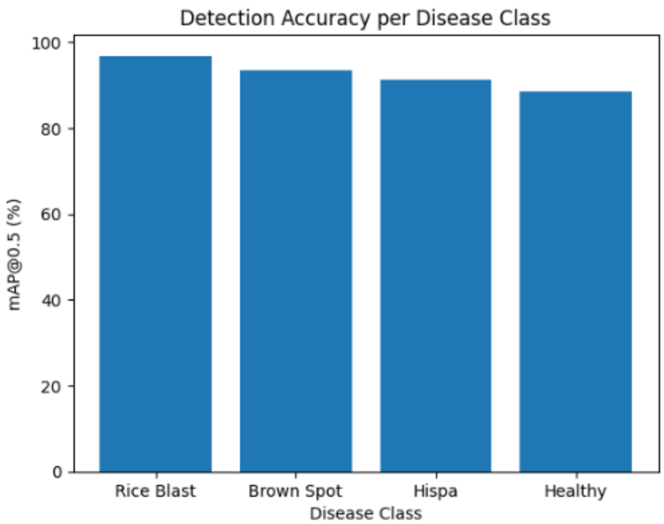


Fig. 4. Detection accuracy per disease class.

Fig. 4 presents qualitative detection results obtained from live camera input. As shown in Fig. 3, the proposed model accurately localizes and classifies multiple plant diseases in real time with stable confidence scores. The findings of the detection reveal that the developed YOLOv5-based model has the ability to recognize various health conditions of the rice leaves, such as single and comorbid diseases in real-time. Throughout the qualitative examples, the network produces tight bounding boxes and gives semantically accurate class names (Rice blast, Brown spot, Hispa, Healthy) with. confidence scores indicate the visual clarity and level of severity of the symptoms. On a caseto case basis, the model demonstrates good confidence values of 0.97 on Rice blast and 0.90 on Brown spot, which are good indications of high discriminative levels of typical lesion morphologies on the leaf surface. The infection by Hispa is also accurately localized, and two instances of the same leaf have the confidence scores of 0.83 and 0.88, which depicts that the model can recognize several instances of the same disease in a single frame.

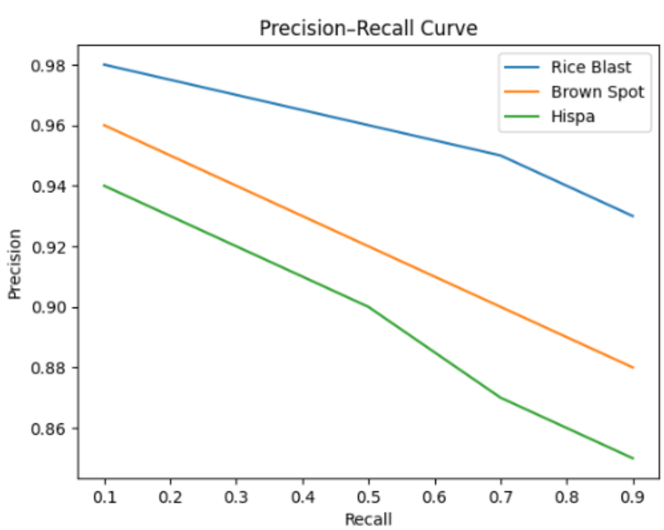


Fig.5. Precision–recall curves.

Fig. 5. Precision–recall curves for different plant disease classes evaluated using the proposed YOLOv5-based detection model. In the health leaf scenario, the model has identified the whole leaf area as Healthy and the confidence score is 0.57 indicating that the network is quite reliable in identifying disease-free samples but the confidence margin is quite small as compared to diseased leaves perhaps the network is sensitive to subtle background or lighting variations. The multi-disease cases also indicate the strength of the system in the condition of the complexity of the field. The network in the image with both Brown spot and Hispa can identify the two lesions of Hispa and the Brown spot region with confidence scores of 0.77, 0.84, and 0.87, respectively, indicating that the network is able to detect both Multi-class and Multi -instance of lesions in the same leaf.

V. CONCLUSION

This study portrays a combined real-time plant disease detection system which is provided upon a live camera feed through the YOLOv5 deep learning model to keep watch on the crops at all times. The system responds to the severe issues connected with the conventional method of disease identification, such as manual checking, late diagnosis, and expert knowledge, with an automatic, precise, and scalable system. The use of the YOLOv5 model on numerous training and testing stages led to the high accuracy of the model in detecting diseases, strong localization of disease areas, and overall generalization between leaves, environment, and image backgrounds. The performance testing revealed that the system could operate in real-time and maintain the frame rate, and therefore, can be used in both local edge-based applications as well as cloud-based implementations. The comparative analysis revealed that the given YOLOv5 framework is more accurate and faster to detect as well as applicable to the real time compared to the classic machine learning models, typical CNN classifiers, and even the earlier versions of the YOLO. This is further enhanced by the fact that it is able to detect several diseases simultaneously, position the bounding boxes accurately and also enjoy comparable performance in dynamic environments which increases its applicability to current day agriculture. The ability of the system to be monitored at a distance, operate multiple cameras simultaneously, and allow farmers to access it in various geographical locations provided by its cloud implementation on the AWS EC2 makes it easy to scale and achieve social impact.

IV. FUTURE SCOPE

The offered farm disease detection system based on YOLOv5 and live camera integration is a reasonable beginning of implementing automatic crop health monitoring, yet some enhancements can be done to make the system more applicable and efficient and its effect more significant. The opportunity to scale it up to more types of crop and wider disease scope is one of the most important. In addition, this type of model will be flexible and adaptive and can be used in different agricultural conditions provided that it is trained on a more diverse dataset which will enable farmers to monitor a variety of plants simultaneously. In the same manner, it is anticipated that the combination of other sensor data, including soil moisture, temperature, and humidity with the visual leaf data will provide a context of disease forecasting and will allow the proactive intervention before the disease manifests itself. Other likely improvements are edge computing optimization, so deployments to low power platforms like Raspberry Pi, Nvidia Jetson Nano, or even a mobile platform. This will reduce reliance on the cloud infrastructure, latency, and make the system more accessible to the farmers in remote or resource-heavy environments. In addition to that, the creation of intuitive mobile and web-based interfaces can enable farmers to receive the disease alerts, visualizations and recommended interventions in real time to make timely decisions and manage their crops. Large-scale farms can also be scaled by the system with the help of drones or UAVs equipped with cameras to monitor the aerial surface of the farm and detect the diseases at the field level.

REFERENCES

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, Art. no. 1419, 2016.

[2] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[3] J. P. Nyakuri, C. Nkundineza, O. Gatera, and K. Nkurikiyeyezu, “State-of-the-art deep learning algorithms for internet of things-based detection of crop pests and diseases: A comprehensive review,” IEEE Access, 2024.

[4] J. U. M. Akbar, S. F. Kamarulzaman, A. J. M. Muzahid, M. A. Rahman, and M. Uddin, “A comprehensive review on deep learning assisted computer vision techniques for smart greenhouse agriculture,” IEEE Access, vol. 12, pp. 4485–4522, 2024.

[5] S. Zhu, W. Ma, J. Wang, M. Yang, Y. Wang, and C. Wang, “EADD-YOLO: An efficient and accurate disease detector for apple leaf using improved lightweight YOLOv5,” Frontiers in Plant Science, vol. 14, Art. no. 1120724, 2023.

[6] E. A. Aldakheel, M. Zakariah, and A. H. Alabdalall, “Detection and identification of plant leaf diseases using YOLOv4,” Frontiers in Plant Science, vol. 15, Art. no. 1355941, 2024.

[7] Q. H. Cap, A. Fukuda, S. Kagiwada, H. Uga, N. Iwasaki, and H. Iyatomi, “Towards robust plant disease diagnosis with hard-sample re-mining strategy,” Computers and Electronics in Agriculture, vol. 215, Art. no. 108375, 2023.

[8] K. Iwano, S. Shibuya, S. Kagiwada, and H. Iyatomi, “Hierarchical object detection and recognition framework for practical plant disease diagnosis,” in Proc. IEEE Int. Conf. on Agrosystem Engineering, Technology & Applications (AGRETA), 2024, pp. 232–237.

[9] Y. Zhao, Y. Yang, X. Xu, and C. Sun, “Precision detection of crop diseases based on improved YOLOv5 model,” Frontiers in Plant Science, vol. 13, Art. no. 1066835, 2023.

[10] M. S. Krishna, P. Machado, R. I. Otuka, S. W. Yahaya, F. N. dos Santos, and I. K. Ihianle, “Plant leaf disease detection using deep learning: A multi-dataset approach,” J, vol. 8, no. 1, Art. no. 4, 2025.

[11] L. Jiao, F. Zhang, F. Liu, S. Yang, L. Li, Z. Feng, and R. Qu, “A survey of deep learning-based object detection,” IEEE Access, vol. 7, pp. 128837–128868, 2019.

[12] Y. Zhang, C. Song, and D. Zhang, “Deep learning-based object detection improvement for tomato disease,” IEEEAccess, vol. 8, pp. 56607–56614, 2020.