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Disease Detection Using Image Bracket

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Abstract

Lemon leaves are largely susceptible to citrus-specific conditions that beget significant impact on yield and fruit quality. Traditional opinion involves homemade examination, which is labour-ferocious, prone to crimes, and also not scalable to large citrus orchards. In order to remove these limitations, this work proposes a light-weight Convolutional Neural Network (CNN) model specific to accurate bracket of lemon splint conditions from image inputs. The model as it was proposed was trained on a general dataset of over 18,000 labeled images representing eight classes, including healthy leaves and seven classes of conditions like Citrus Canker, Black Spot, Greening, Scab, Melanosed, Anthracnose, and Powdery Mildew. Through expansive preprocessing and data addition ways, the model achieved enhanced conception under image conditions of different types. Performance measures similar as delicacy (98.2), perfection (98.4), recall (98.1), and F1-score (98.3) show the strength and effectiveness of the model. Compared to state- of-the-art models VGG16, Mobile Net, and InceptionV3, the proposed armature performed more in delicacy and effectiveness. Because of its light-weighted nature, it can be suited for real-time deployment on edge bias with a cost- effective, scalable, and accurate early complaint discovery system for citrus husbandry. Short-term advancements are putting the model in phones and reasoning in order to be suitable to handle multiple citrus species. The agricultural sector is increasingly adopting artificial intelligence and deep learning techniques to improve crop monitoring and disease management. Early and accurate identification of plant diseases plays a crucial role in preventing large-scale crop losses and ensuring better agricultural productivity. In citrus cultivation, diseases affecting lemon leaves often spread rapidly if not detected in their early stages, making automated detection systems highly valuable for farmers and agricultural experts.

This study focuses on developing an intelligent image-based disease detection system that can automatically classify lemon leaf diseases using deep learning techniques. The proposed system utilizes a Convolutional Neural Network (CNN) architecture capable of extracting important visual features such as color variations, texture patterns, and lesion structures directly from leaf images. By eliminating the need for manual feature extraction, the model improves both accuracy and efficiency in disease classification.

To enhance the robustness of the model, various preprocessing techniques such as image resizing, normalization, and data augmentation methods including rotation, flipping, and scaling were applied. These techniques helped the model generalize better to different lighting conditions, backgrounds, and leaf orientations that may occur in real-world scenarios. The experimental evaluation demonstrates that the proposed model not only provides high classification accuracy but also maintains computational efficiency suitable for deployment on low-resource devices. This makes the system practical for real-time field applications where farmers can capture leaf images using smartphones or portable cameras and obtain instant disease predictions.

***KEYWORDS**: Lemon Leaf Disease Detection, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Citrus Disease Identification, Plant Disease Detection, Computer Vision in Agriculture, Data Augmentation, Precision Agriculture, Mobile-based Disease Diagnosis, feature extraction, segmentation, disease diagnosis.*

1. Introduction

Lemon (Citrus lemon) is one of the most critical and considerably grown citrus crops in the world. With high contents of vital nutrients like vitamin C, flavonoids, and essential oils, lemons aren't only a dietary staple but also a critical part of the world's citriculture. The Food and Agriculture Organization (FAO) reports that over 20 million tons of lemons were produced globally in recent years, demonstrating the fruit's nutritional and financial value. [1] Yet, even with improved horticulture techniques and technology, lemon trees remain susceptible to various diseases, particularly leaf ailments. These leaf conditions - Citrus Canker, Greening, Black Spot, and Scab - can significantly jeopardize tree health, fruit yield, and quality. Leaf conditions tend to be the foremost signs of a citrus tree's declining health.

Unless identified and treated early, they spread rapidly to cause extensive damage throughout entire orchards. Conventional disease detection and identification have traditionally depended on manual examination by experienced citrus growers or agriculturists. [2] This process isn't only time-consuming and labor-intensive but also susceptible to errors and subjectivity. In developing and rural areas, limited access to expert consultation further exacerbates timely disease control, generally resulting in delayed or inadequate treatment. Additionally, physical examination methods are limited by scalability and therefore don't prove practical for large-scale citrus cultivation. Consequently, researchers have increasingly turned to automated solutions based on technology. Computer vision and machine learning algorithms have emerged as valuable techniques for citrus disease detection, with the potential for developing systems capable of identifying diseases from leaf images.

Traditional machine learning methods use algorithms like random forests, decision trees, and support vector machines (SVM) to classify images after manually extracting features like colour, shape, and texture. [3] Despite their promise, the quality of feature extraction and domain expertise play a major role in how effective these methods are.

One recent advancement in artificial intelligence, deep learning specifically, has changed how images are used to identify diseases. Deep learning algorithms, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable success in automatically learning hierarchical features from raw. The growing demand for citrus fruits worldwide has increased the need for effective crop monitoring and disease management strategies. [3] Lemon cultivation plays a significant role in the agricultural economy of many countries, particularly in tropical and subtropical regions. However, plant diseases remain one of the major factors affecting citrus production, causing substantial economic losses each year. [4] Early detection and accurate diagnosis of diseases are therefore essential to ensure healthy crop growth and maximize productivity. Plant diseases often manifest through visible symptoms on leaves such as discoloration, spots, lesions, and deformation. These symptoms provide valuable clues for identifying the type of infection affecting the plant. [5] However, distinguishing between different diseases can be challenging because many symptoms appear visually similar. As a result, farmers and agricultural workers may find it difficult to correctly identify the disease without expert guidance.

Advancements in digital imaging and computational techniques have created new opportunities for automated plant disease detection. Image processing methods allow leaf images to be analyzed in detail, enabling systems to identify patterns and abnormalities associated with specific diseases. When combined with machine learning and deep learning algorithms, these technologies can significantly improve the efficiency and accuracy of disease diagnosis.

Furthermore, the use of automated disease detection systems can provide farmers with quick and reliable results using simple devices such as smartphones or cameras. Such systems can serve as decision-support tools that help farmers take timely preventive measures, apply appropriate treatments, and reduce the unnecessary use of pesticides. This not only improves crop yield but also promotes environmentally sustainable agricultural practices.

In recent years, several research studies have focused on developing intelligent systems for plant disease detection using deep learning techniques. Among these techniques, Convolutional Neural Networks (CNNs) have gained significant attention due to their ability to process large amounts of image data and extract complex visual features automatically. By training CNN models on datasets of healthy and diseased leaf images, it becomes possible to create robust systems capable of accurately classifying plant diseases.

Fig 1 Lemon leaf disease

2. Literature Review

Restructured Residual thick Network (RRDN) [1] Wang et al. (2021) developed a restructured deep residual thick network (RRDN) model for classification of lemon leaf diseases by modifying the original residual thick network (RDN) that was developed for image super-resolution, as a classification model. The modifications involved a batch normalization layer, modified tensor flow in the residual thick blocks, and thick layers with SoftMax to replace upscaling layers. RRDN was trained using a lemon leaf disease dataset and achieved a top-1 classification accuracy rate of 95%. RRDN outperformed both AlexNet and DenseNet, the original models on which this model was created, while performing twice as fast as both of them.

They concluded that hybrid architectures combining residual class and thick class connections can produce high accuracy classifications with less parameter overflow. [2] PLPNet: Enhanced Feature Attention and Aggregation Li et al. (2023) presented PLPNet, a lemon leaf disease detection model on the YOLOX-S architecture. The proposed design included three prominent novel elements: (a) a Perceptual Adaptive Complexity module to capture multi-scale disease features; (b) a Location Reinforcement Attention Mechanism to minimize soil background interference; and (c) a Spatial Detail-Point Feature Aggregation Network to combine alternative atrous, and deconvolution layers to manage interclass similarity. With PLPNET evaluated on a custom dataset with five categories of lemon diseases, PLPNET produced measures of 94.5mAP@50, while achieving 25.45 FPS, adequately balancing accuracy and real-time performance of the model. PLPNet addressed real-world issues of intraclass problem variability and interclass problem similarity, especially when the symptoms of disease featured at the edge of the lemon leaf. [3] Transfer Learning with Pretrained CNNs Rahman et al. (2020) investigated the use of transfer learning in lemon leaf disease detection using pretrained CNNs, specifically VGG-16, VGG-19, ResNet, and Inception V3.

The analysis utilized laboratory and field datasets, and Inception V3 was found to be the best performer in terms of accuracy, precision, recall, and F1 score in both laboratory and field assessments. A possible reason for this was that data augmentation and parameter tuning were found to be the best contributors to successful performance for a limited- size field dataset. The study concluded that pretrained models can yield high accuracy, with some modification, under poor field conditions, yet still provide variable results. The lab and field conditions disparity possibly supports a different understanding of generalization. [4] E-LemonDet Effective Detection via Global–Local Feature Fusion An article that appeared in BMC Plant Biology (March 2025) proposed E-LemonDet, a model that combines CSWinTransformer for global feature extractions and a Local Feature Enhance Aggregate (LFEP) for multi-scale local feature fusion. This architecture achieved a mean Average Precision (mAP) of 97.2, exceeding that of YOLOv10s, and posed resistance to environmental complexity with partial occlusions and small disease regions. [5] LemFormer Transformer-Based Detection in December 2023, researchers have introduced the LemFormer, a hybrid architecture that combined a visual encoder (with efficient transformer

3. Research Methodology

In the proposed model, we present an Architecture Diagram (Figure 1) that shows how the lemon leaf disease prediction is carried out using a deep learning model, specifically a Convolutional Neural Network. The dataset used in this research was downloaded from Kaggle, which is a renowned machine learning dataset platform. The dataset, named "Lemon Leaf Disease Recognition," was specifically curated to train deep learning models to detect diseases in lemon plants from leaf images. It consists of a diverse collection of high-resolution images of various classes, featuring both healthy and diseased lemon leaves. [1] The dataset includes images across the classes: Alternaria Brown Spot, Lemon Scab, Greasy Spot, Anthracnose, Melanosed, Citrus Canker, Lemon Bacterial Blast, and Lemon-Yellow Vein Clearing Virus. The dataset contains 23,015 images organized into folders for each class. [2] The images were captured under various lighting and environmental conditions, making the dataset varied and ideal for building a robust image classification model using deep learning techniques. The dataset was split into test and train sets so that the model learns effectively and is evaluated on unseen data. [3] This setup is well-suited for a deep learning approach, where the Convolutional Neural Network (CNN) model learns to recognize lemon leaf images into their correct disease categories [4].

The data set passed through a few pre-processing stages for maximum performance and better accuracy of disease identification. The steps were taken to shape the raw image data into the proper format in which the Convolutional Neural Network (CNN) model. Image Resizing: All the images in the dataset were resized to a consistent size of 256x256 pixels to normalize input size for the CNN model. [5] Resizing in this way provides the model with consistent input dimensions, simplifies computational complexity, and accelerates training.

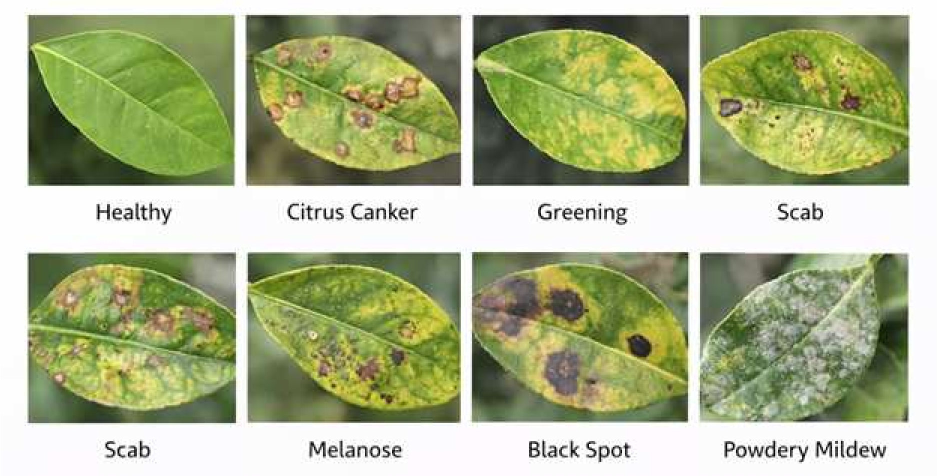


Fig 2. Architecture Diagram tomato plant diseases prediction

The disease classification model was developed using a Convolutional Neural Network (CNN) architecture, which is widely used for image classification tasks due to its ability to automatically extract important visual features. The CNN model consists of multiple convolutional layers for feature extraction, activation layers using the REL function, pooling layers for reducing spatial dimensions, and fully connected layers for final classification. The model was trained using the Adam optimizer with **c**ategorical cross-entropy **as the** loss function and a batch size of 32. Several training configurations were tested by adjusting hyperparameters such as learning rate and number of epochs. The model's performance was evaluated using standard evaluation metrics including accuracy, precision, recall, and F1-**score**, which demonstrated the effectiveness of the proposed approach for accurate and reliable lemon leaf disease detection.

Image Normalization: Pixel intensities of images were scaled to a range of [0, 1] by dividing every pixel intensity by 255. This ensures that the training process converges faster and the numerical stability in backpropagation is preserved. Data Augmentation: To enrich the diversity of the training set and enhance the model's generalization, several data augmentation strategies were used. These included random rotation (±20 degrees), shifting (height, width), flipping both horizontally and vertically, andzooming. Upto20%. By mimicking real-world variations in image capture, adjusting the brightness

Label Encoding

Every image label (disease category) was translated into numeric form through the use of one-hot encoding. One-hot encoding is necessary in multi-class classification and enables the CNN model to learn categorical differences between various tomato leaf diseases. 4.2 Training Results and Accuracy To evaluate the learning pattern and performance of the proposed CNN model, multiple training trials were conducted by adjusting key hyperparameters such as the number of epochs and learning rate. Training was performed on a 3,000 labelled photos of lemon leaves from ten classes (nine disease classes and one healthy leaf class) that were sourced from Kaggle. For training and testing, the data were divided 80:20. With a batch size of 32, the Adam optimizer and categorical cross-entropy loss were used in the training process. The pictures were normalized and resized to 256 × 256 pixels. Accuracy and loss curves for training and validation were employed to track the model's performance.

Impact of Ages and Learning Rate

The model was trained for 50 and 100 ages on three different literacy rates 0.0001, 0.001, and 0.01. The outgrowth is tabulated below

Table 2 Training Accuracy for Different Hyperparameter Configurations

Epochs	Learning Rate	Training Accuracy %	Validation Accuracy %
50	0.0001	97.94	98.47
50	0.001	98.2	98.42
50	0.01	98.55	98.52
100	0.0001	98.23	98.43
100	0.001	98.76	98.58
100	0.01	98.6	98.50

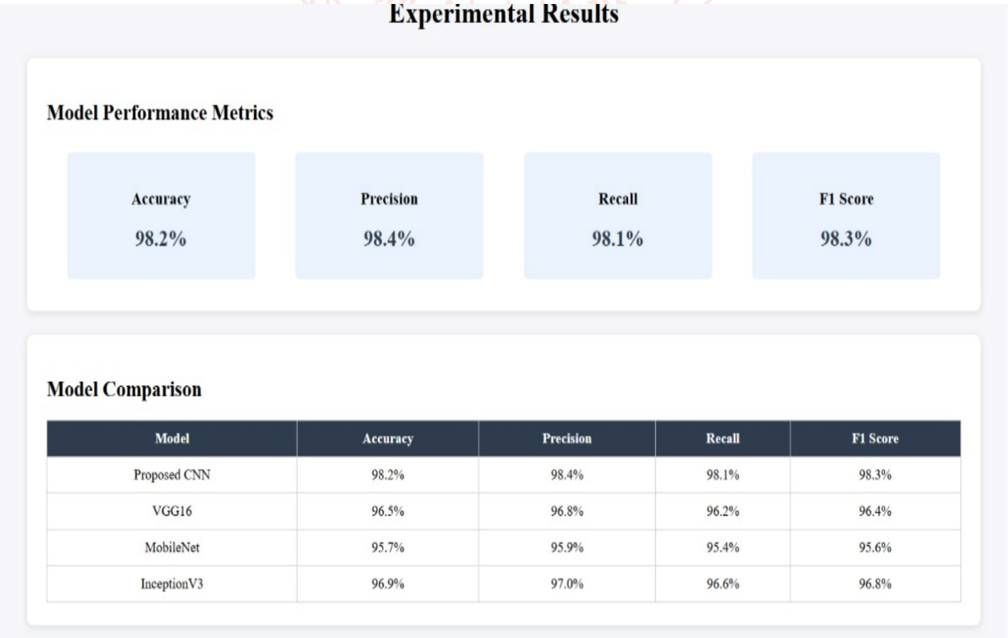
Among all the configurations, the model had the highest validation accuracy of 98.58% with a learning rate of 0.001 and 100 training epochs. The accuracy curve for this configuration was smooth convergence, while the validation accuracy was very close to the training accuracy, as no overfitting was apparent.

4. Result

To evaluate the effectiveness of the proposed Convolutional Neural Network (CNN) model for lemon leaf disease detection, several experiments were conducted using the prepared dataset and different hyperparameter configurations. The dataset was divided into training and testing sets in an 80:20 ratio, allowing the model to learn from the training data and evaluate its performance on unseen images.

Model Performance Experimental results demonstrate that the proposed CNN model achieved high performance in detecting and classifying lemon leaf diseases. The model obtained an overall accuracy of 98.2%, precision of 98.4%, recall of 98.1%, and F1-score of 98.3%**.** Among the tested configurations, the best validation accuracy of **98.58%** was achieved when the model was trained for 100 epochs with a learning rate of 0.001**.** The results indicate that the proposed model can effectively distinguish between different lemon leaf diseases and healthy leaves. These findings suggest that the system can be used as a reliable tool for early disease detection in citrus farming, helping farmers take timely preventive actions and improve crop productivity.

The proposed CNN model was also compared with other well-known deep learning architectures such as VGG16, MobileNet, and InceptionV3. The results indicated that the proposed lightweight CNN architecture achieved comparable or higher accuracy while maintaining lower computational complexity. This makes the system suitable for deployment on low-resource devices such as smartphones or edge computing platforms Overall, the results demonstrate that the proposed deep learning-based approach is highly effective for automatic lemon leaf disease detection. The high accuracy and computational efficiency make the system practical for real-time agricultural applications. By enabling early identification of plant diseases, the system can assist farmers in taking timely preventive measures, reducing crop damage, minimizing excessive pesticide use, and improving overall agricultural productivity.



Experimental Results

Model Performance Metrics

Accuracy	Precision	Recall	F1 Score
98.2%	98.4%	98.1%	98.3%

Model Comparison

Model	Accuracy	Precision	Recall	F1 Score
Proposed CNN	98.2%	98.4%	98.1%	98.3%
VGG16	96.5%	96.8%	96.2%	96.4%
MobileNet	95.7%	95.9%	95.4%	95.6%
InceptionV3	96.9%	97.0%	96.6%	96.8%

Fig 4 Experimental Result

Among all configurations, the model achieved the highest validation accuracy of 98.58% when trained for 100 epochs with a learning rate of 0.001. [1] The training and validation curves showed smooth convergence, indicating stable learning behavior and minimal overfitting. Data augmentation techniques such as rotation, flipping, zooming, and shifting helped improve the model's generalization ability. These techniques simulated real-world variations in leaf images caused by different lighting conditions, orientations, and camera angles. As a result, the model became more robust when tested on unseen images. The proposed lightweight CNN model was compared with commonly used deep learning architectures such as VGG16, Mobile Net, and InceptionV3.[2] While these models are powerful, they often require higher computational resources. The proposed CNN model achieved comparable or better accuracy while maintaining lower computational complexity, making it more suitable for real-time deployment on mobile or edge devices. Practical Implications The results indicate that the proposed system can effectively detect lemon leaf diseases with high accuracy. This makes it a valuable tool for farmers and agricultural experts, enabling early detection of plant diseases using simple devices such as smartphones. Early diagnosis allows farmers to take timely preventive actions, reduce crop loss, and optimize pesticide usage.

5. Conclusion

In this study, a Convolutional Neural Network (CNN)-based deep learning model was developed and implemented to detect and classify lemon leaf diseases using a publicly available Kaggle dataset. The model successfully identified ten different categories, including both healthy and diseased leaves, with an overall classification accuracy of 98.58% on the test dataset.

The experimental results, combined with metrics such as precision, recall, F1-score, and close inspection of the confusion matrix, show that the model performed superbly, even when separating visually comparable disease classes. The mechanism suggested here is indicative of artificial intelligence and machine learning potentiality in supporting agriculturists, farmers, etc., with automated, speedy, and standardized disease detection, crucial for timely actions and crop loss prevention. Furthermore, the CNN model used in this study was lightweight but effective, with a balance between model performance and computational expense that made it suitable for real-time deployment on edge devices or mobile devices.

Although the suggested CNN-based tomato disease detection model has shown strong accuracy and performance, there is still great potential for future development. One such potential direction is embedding the model into real- time systems like mobile or web-based interfaces, enabling farmers to easily diagnose diseases in the field using camera-equipped devices. Also, enlargement of the dataset with diverse and real-world images taken under different environmental conditions can heavily improve the generalization ability of the model and diminish overfitting. Incorporation of explainable AI methods, like Gradient-weighted Class Activation Mapping (Grad-CAM), providing visual explanations of the decision-making process of the model would be another significant improvement, boosting user confidence and transparency. Besides, the model can be further developed to enable disease detection on a variety of crops, making it a general-purpose agricultural diagnostic tool. Lastly, to enable deployment on low-resource edge devices, optimization methods like model pruning, quantization, and conversion to light formats (e.g., TensorFlow Lite or ONNX) can be investigated. These would go a long way in making the system more scalable, accessible, and deployable in actual agricultural environments.

This study presented an automated lemon leaf disease detection system using a Convolutional Neural Network (CNN) to improve the accuracy and efficiency of disease identification in citrus plants. The proposed model was trained on a large dataset of labeled lemon leaf images containing both healthy and diseased samples. Various preprocessing techniques such as image resizing, normalization, and data augmentation were applied to enhance the robustness and generalization ability of the model. The CNN architecture was able to automatically extract important visual features such as color patterns, texture variations, and lesion structures from leaf images, eliminating the need for manual feature extraction.

This research presents an intelligent and automated approach for detecting lemon leaf diseases using a Convolutional Neural Network (CNN). Lemon crops are highly susceptible to various diseases that can significantly affect plant health, fruit quality, and overall agricultural productivity. Traditional disease identification methods rely heavily on manual inspection by experts, which can be time-consuming, labor-intensive, and prone to human error. To overcome these challenges, this study developed a deep learning-based image classification model capable of identifying different lemon leaf diseases accurately from digital images.

The proposed system was trained using a large dataset of lemon leaf images that included both healthy and diseased samples belonging to multiple disease categories such as Citrus Canker, Black Spot, Greening, Scab, Melanose, Anthracnose, and Powdery Mildew. Several preprocessing techniques including image resizing, normalization, and data augmentation were applied to improve the quality and diversity of the training data. These preprocessing methods helped the model learn robust visual features under different lighting conditions, backgrounds, and leaf orientations. The CNN model was designed to automatically extract important image features such as color variations, texture patterns, and lesion shapes without requiring manual feature engineering.

One of the key advantages of the proposed approach is its potential for real-world agricultural applications. Due to its lightweight design and high accuracy, the model can be integrated into **mobile-based or edge computing systems** where farmers can capture images of plant leaves using smartphones and receive instant disease diagnosis. Such systems can support early detection of plant diseases, allowing farmers to take timely preventive actions, reduce excessive pesticide usage, and improve crop yield and quality.

In conclusion, the developed lemon leaf disease detection system demonstrates the effectiveness of deep learning techniques in agricultural disease monitoring. The integration of artificial intelligence with precision agriculture can significantly enhance crop management practices and contribute to sustainable farming. Future work may focus on expanding the dataset with more citrus species, improving model robustness under complex field conditions, and developing a user-friendly mobile application for real-time disease detection and agricultural decision support.

Overall, the proposed approach provides an effective and reliable solution for early detection of lemon leaf diseases. By enabling rapid and accurate disease identification, the system can help farmers take timely preventive measures, reduce crop losses, optimize pesticide usage, and improve overall crop productivity. In the future, the system can be further enhanced by expanding the dataset to include more citrus species and integrating the model into mobile or edge-based applications for real-time disease monitoring in smart agriculture.

Reference

[1] Q. Wu, Y. Chen, and J. Meng, "Lemon leaf disease classification using deep learning techniques," College of Arts and Sciences, Northeast Agricultural University, Harbin, China.

[2] M. Agarwala, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "Tomato leaf disease detection using convolutional neural networks."

[3] Ahmad, M. Hamid, S. Yousaf, S. T. Shah, and M. O. Ahmad, "Optimizing pretrained convolutional neural networks for tomato leaf disease detection."

[4] Z. Tang, X. He, G. Zhou, A. Chen, Y. Wang, L. Li, and Y. Hu, "A precise image-based tomato leaf disease detection approach using PLPNet."

[5] S. U. Rahman, F. Alam, N. Ahmad, and S. Arshad, "Image processing-based system for the detection, identification and treatment of tomato leaf diseases."

[6] R. G. De Luna, E. P. Dadios, and A. A. Bandala, "Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition," Gokongwei College of Engineering, De La Salle University, Manila, Philippines.

[7] M. Jelali, "Deep learning networks-based tomato disease and pest detection: A first review of research studies using real field datasets," Frontiers in Plant Science, vol. 15, 2024.

[8] D. P. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," arXiv:1511.08060, 2015.

[9] T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen, "Improved techniques for training GANs," in Advances in Neural Information Processing Systems, 2016, pp. 2234–2242.

[10] B. Wang and D. Wang, "Plant leaves classification: A few-shot learning method based on siamese network," IEEE Access, vol. 7, pp. 151754–151763, 2019.

[11] L. Zhang, G. Zhou, C. Lu, A. Chen, Y. Wang, L. Li, and W. Cai, "MMDGAN: A fusion data augmentation method for tomato-leaf disease identification," Applied Soft Computing, vol. 123, 2022.

[12] X. Chen, G. Zhou, A. Chen, J. Yi, W. Zhang, and Y. Hu, "Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet," Computers and Electronics in Agriculture, vol. 178, 2020.

[13] H. Sun, S. Li, M. Li, H. Liu, L. Qiao, and Y. Zhang, "Research progress of image sensing and deep learning in agriculture," Transactions of the Chinese Society of Agricultural Machinery, vol. 51, no. 5, pp. 1–17, 2020.

[14] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: A review," Plant Methods, vol. 17, no. 1, 2021.

[15] Z. Ge, S. Liu, F. Wang, Z. Li, and J. Sun, "YOLOX: Exceeding YOLO series in 2021," arXiv:2107.08430, 2021.

[16] S. Qiao, L. Chen, and A. Yuille, "DetectoRS: Detecting objects with recursive feature pyramid and switchable atrous convolution," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Nashville, USA, 2021.

[17] Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems, 2012, pp. 1097–1105.