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Efficient and Precise Disease Detection in Tomato Plants Using YOLOv7 for Automated Recognition

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***Abstract*— Tomato plants are very vulnerable to diseases that leads to it being spoiled or resulting in bad yield quality which causes lot of trouble to the farmers. Usually, the farmers are trained to identify the diseases using manual observation, which is proven to be inefficient since it requires much training and experience to be able to identify these diseases at a glance. Therefore, we are proposing this research, an efficient framework for tomato plant disease detection using automated recognition using YOLOv7 deep learning model. It uses superior convolutional neural network architecture, which identifies and classifies multiple leaf diseases accurately under complex field conditions. Thus, it is more faster and accurate than traditional methods. This work aims to implement technical developments like AI, Object detection to make the task of identifying diseases easily and efficiently.**

Keywords—YOLOv7, Tomato Plant Disease Detection, Image Pre-processing, Deep Learning, Convolutional Neural networks

I. INTRODUCTION

Diseases in crops are one of the most difficult challenges to agriculture today and potentially more devastating threats to global food production. Tomato is one of the most common plants which is susceptible to various diseases caused by bacteria, fungus, and viruses. These diseases can cause serious losses in yield and quality which results in considerable economic and financial losses to farmers. For this reason, detecting the diseases early would be an enormous advantage to farmers. It helps them to eliminate the cause and take counter measures to avoid financial ruin. Traditional methods usually require high expertise in agricultural knowledge and plant diseases. Also it requires a large amount of labor to cover a big field of plants. If they are manually observing and identifying the diseases, this would cost a lot of money to be able to provide salary to the labours making it an inefficient way to approach this issue.

[1][2]The goal of this research is to enhance the detection of diseases in tomato plants using automated recognition which are faster and accurate. Such techniques will stand the test of field conditions, including hyper-specialized Convolution Neural Network (CNN) architecture in YOLOv7 to detect and classify the diseases in real-time, or multiple diseases simultaneously. By considering the field conditions, such as lack of light, noisy background, and occlusion variances, this model is yet reason to be in supporting the proposed sustainable agriculture. Machine learning provides adaptability and improvement for precision farming. As previously stated, tomato is most vulnerable among crops which are prone to a wide range of diseases such as Septoria Leaf Spot, Early Blight. Tomato Leaf Yellow Curl Virus, Bacterial Spot, Tomato Leaf Miner, Tomato Mosaic Virus, Late Blight, Spider Mites, Leaf Mold, Target Spot.

These diseases severely affect crop yield and its quality, resulting in economic losses for farmers and posing a threat to food security. Early detection of these diseases is critical, as it allows the farmers to prevent widespread damage and ensure the health of the crops. With the development of advanced imaging technologies, it is easier to tackle these issues. Further in this paper, we will explore the diseases impacting tomato plants and highlight the effective use of these transformative technologies to address the associated issues.

II. LITERATURE SURVEY

In this literature survey, we have mentioned the different types of projects and their content like the methodology, features,and the challenge they have faced in that we have implemented and to reduce the time and the easy way to find the disease detection.

Detection of Plant Disease Using Machine Learning and Deep Learning Algorithms (2023) - IEEE Access

This study evaluates and compares traditional machine learning models such as Random Forest (RF), Support Vector Models (SVM) with deep learning architectures such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and ResNet. They identified limitations in accuracy and efficiency in handling complex data or varying lighting, multi class overlaps. Also they found that conventional machine learning models struggle with high dimensional data.

Enhanced Crop Disease Detection With EfficientNet Convolutional Group-Wise Transformer (2024) - IEEE Access

This paper introduces the hybrid EfficientNet Group Wise Transformer (EGWT) model which combines efficient for global context modelling. It also uses compound scaling for balanced depth, width and resolution scale. Also local features such as edges, textures and lesion shapes are extracted using this convolutional blocks. They face challenges such as high computational complexity in pure transformers and deep CNNs. Other limitations includes subjectivity in traditional visual inspection methods. We are referring and learning about the limitations and challenges of using traditional machine learning models.

MSCPNet: A Multi-Scale Convolutional Pooling Network for Maize Disease Classification (2025) - IEEE Access

In this research, they are proposing a lightweight hybrid network with a truncated MobileNetV2 backbone which is integrated with a multi scale convolutional poolformer block. Through this, they are able to achieve generic low level features and also multi scale aggregation via convolutional branches for less variations. Also they face few challenges such as loss of fine grained spatial information during traditional pooling which adds a subtle blur textures.

Precision Agriculture Through Deep Learning: Tomato Plant Multiple Diseases Recognition With CNN and Improved YOLOv7 (2024) - IEEE Access

In this paper, they are using YOLOv7 which is enhanced with SimAM (Simple Parameter free Attention Module) /DAiAM (Digital Image Adaption Module) attention modules and improved MPConv for better feature extraction and reduced information loss. They are trained on plantvillage tomato datasets with flowcharts. Since they are using SimAM/DAiAM, it is easier for them to highlight disease specific patterns. It also reduces information loss through MPConv's efficient convolution. Here they are facing challenges such as overlapping symptoms across diseases which hinders accurate identification. They also face information loss in deep networks during downsampling, leading to blurred detections in field images.

III. RELATED WORKS

Tomato (Solanum lycopersicum) is globally one of the most widely cultivated vegetables. It serves as a staple in diets of many people and it is a key crop in horticulture, with high nutritional value including vitamins A and C, antioxidants like lycopene. Tomato contributes in a lot of markets around the globe such as consumption, processing and export markets, valued at billions in the economy. Also its production face various threats from diseases caused by fungi, bacteria and viruses. It leads to substantial yield losses in severe cases and it reduces fruit quality. Also it impacts the farmers economically, particularly in regions which mainly a agricultural nation like India. Common pathogens of these diseases include fungi such as Septoria lycopersici, Alternaria solani and bacteria such as Xanthomonas species, and viruses like Tomato Yellow Leaf Curl Virus (TYLCV), which affect leaves, stems, and fruits, disrupting photosynthesis, nutrient uptake, and overall plant health causing the plant to get rotten or produce less quality yield.

1) Septoria Leaf Spot

[3]Septoria leaf spot (Septoria lycopersici) is a fungal disease. It causes small circular spots with dark border in tomato leaves leading to reduction of photosynthesis and causing defoliation of said plant. It is spread through overhead water splashing rain and warm or wet conditions. It is tackled by using methods involving improving air circulation, crop rotation, removing debris and avoiding overhead watering. Also applying fungicides such as mancozeb can help in reducing the chances of septoria leaf spots from appearing in the tomato plant leaves.

Fig. 1. Septoria Leaf Spot on Tomato Leaves

2) Early Blight

[4]Early blight is caused by the fungus Alternaria solani (also known as A. tomatophila). It is a foliar fungal disease which causes premature death or leaf drop and reduced yield. This early blight is caused by soil born fungus and further grows with warm, wet weather and plant stress. It also

spreads using the wind and flying debris caused by the wind. This fungus can survive the winter in soil or on other plants like potatoes, which means it keeps coming back year after year and is a real headache for tomato growers everywhere. The symptoms of this disease can be identified by spotting dark brown or black spots onto the lower leaves. As early blight starts to grow, these spots grow and the leaves will turn yellow and drop off in the process called the defoliation. Once the plant loses enough leaves, it can't photosynthesize properly, so it doesn't have the energy to grow or produce good fruit. It can be avoided by using crop varieties which are resilient to early blight such as mountain fresh. Otherwise rotational crops can be used to reduce the chances of early blight from appearing in tomato plant leaves. Other methods used to tackle early blight are enhancing air circulation, removing debris and improving drainage. Also, the use of fungicides such as pyraclostrobin routinely can help in tackling the early blight disease in tomato plants.

Fig. 2. Early Blight on Tomato Leaves and Fruit

3) Tomato Yellow Leaf Curl Virus

[5]Tomato Yellow Leaf Curl Virus (TYLCV) is a real menace for tomato growers. It is caused by a virus named after the disease Tomato yellow leaf curl virus (Begomovirus) which spreads fast by means of insects such as the whitefly (*Bemisia tabaci*) and also by persistent transmission. It stunts growth of the tomato plant and eliminates fruit growth. This can be identified by upward leaf curling, yellowing of leaves and reduced flowering. It mainly affects young leaves and newly growing tips. This virus can be avoided by planting resilient varieties and weed removal. Also screens can be used to catch whiteflies which is the carrier of this virus. Insecticides such as imidacloprid can be used to get rid of these insects which is the cause of this disease. It spreads primarily via whitefly and sometimes through seeds. These symptoms can be seen 15-30 days after the initial infection. It also spreads rapidly in high vector populations.

Fig. 3. Tomato Yellow Leaf Curl Virus Symptoms on Leaves

4) Bacterial Spot

[6]Bacterial Spot (Xanthomonas campestris pv. vesicatoria) is caused by a bacterial infection which is spread via rain, wind or contaminated seeds and tools and it has symptoms like small, water soaked spots on leaves and fruit that turn dark brown. It causes defoliation in severe cases. For tackling this disease we can use methods such as using disease-free seeds and transplants, practicing crop rotation, and applying copper-based bactericides which can reduce the chances of Bacterial spot from occuring.

Fig. 4. Bacterial Spot on Tomato Leaves

5) Tomato Leaf Miner

The Tomato Leaf Miner (Tuta absoluta) can damage the tomato plants to the point where it can lead to reduced photosynthesis, stunted growth, and significantly lower yields, sometimes causing more loss. This leaf miner disease can be identified through various symptoms and some of which are irregular tunnels (mines) in leaves, and sometimes there are holes present in fruit, and drying of leaf could also be accounted as one of the symptoms of tomato leaf miner disease which can be identified by observing the tomato leaves. It causes the insect pest whose larvae feed inside leaves and fruits, thriving in warm, dry conditions.

Fig. 5. Tomato Leaf Miner Symptoms on Leaves

6) Tomato Mosaic Virus

Tomato mosaic virus (ToMV) is a plant pathogenic virus which can results in a loss of yield and this virus can spread easily and rapidly. It can be identified using some symptoms like Mosaic or mottled light and dark green patches on leaves, leaf curling, and reduced fruit quality and Main reason for the spread of this virus is by contaminated hands, tools, and infected seeds.

Fig. 6. Tomato Mosaic Virus Symptoms on Leaves

7) Late Blight

Tomato Late Blight (Phytophthora infestans) is a destructive disease and the oomycete Phytophthora infestans that creates water-soaked spots on leaves and stems, which rapidly turn brown it has symptoms like large, irregular, water-soaked spots on leaves that turn brown and black. white mold under leaves and it causes Fungal-like organisms favored by cool, wet weather; spreads rapidly in moist conditions.

Fig. 7. Tomato Late Blight Symptoms on Leaves

8) Spider Mites

Tomato spider mites (Tetranychus urticae) sap-sucking pests that cause damage to tomato plants, especially in hot, dry weather. It has symptoms like yellow or bronze stippling on leaves, webbing under leaves, and leaf drop and its causes tiny mites thrive in hot, dry conditions; spread by wind or infested plants. In the beginning stages, we can notice tiny white and yellow spots on the leaves or even notice tiny holes. As it grows we can also notice that silky spider webs have been formed around the leaves and stem of the plant. Once the infestation is heavy we can see that the leaves are turned dusty pale and fully covers itself with webbing. Hence the name spider mites is given to this disease.

Fig. 8. Spider Mites Symptoms on Tomato Leaves

9) Leaf Mold

Tomato Leaf Mold Passalora fulva (Cladosporium fulvum) Its spreads rapidly in high humidity and can lead to premature defoliation and reduced yield, and sometimes affects fruit, stems, and blossoms the symptoms like Pale green or yellow spots on upper leaf surface and olive-green mold underneath and it's causes Fungal disease favored by high humidity and poor air circulation in greenhouses.

Fig. 9. Leaf Mold on Leaves of Tomato

10) Target Spot

Tomato Target Spot(Corynespora cassiicola) that affects tomato plants, especially in warm, wet, and humid conditions. It is characterized by the appearance of circular, brown lesions on leaves and stems that develop concentric rings, resembling a target.the symptoms like Brown circular spots with concentric rings on leaves, stem lesions, and fruit spots and it's causes Fungal infection encouraged by warm, humid weather and wet foliage.

Fig. 10. Target Spot on Tomato Leaves

IV. PROPOSED SYSTEM

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[7][8]To give an overview of the framework proposed to achieve efficient and accurate disease detection in tomato plants, Leaf detection is one of the functions that would be achieved through this sophisticated multi-stage image processing architecture which will then lead to a deep learning model of the YOLOv7 type. The system is designed with the purpose of fully automating the recognition of the main tomato diseases, such as Septoria Leaf Spot, Early Blight, Tomato Leaf Yellow Curl Virus (TYLCV), and Bacterial Spot-the idea being to overcome the inefficiencies and inaccuracies of the traditional manual inspection methods that rely on expert visual assessment. Usually the process of doing this starts with acquiring high resolution images, this acquisition is achieved using methods like capturing images using standard digital cameras, drones or surveillance cameras or even using mobile phones. These images can be captured under various field conditions such as fog, rain, sunny, etc. Also capturing different perspectives can help immensely. Next step is to process the images which are acquired. This is done to improve the quality of captured images and to isolate and clearly define features of the leaves while removing noisy images, background clutter, and overlapping leaves. We are using few techniques such as seperating RGB channel of images and grayscale conversion for form recognition of the leaves and we also use sharpening filters for edge detection before passing all of these pre-processed images to model training. By providing a clearly defined and well processed image, we can increase the efficiency of the model YOLOv7. It helps in easier and accurate identification of the diseases.

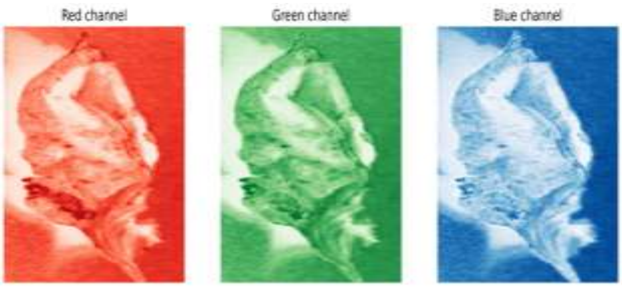

Fig. 11. RGB Channel Separation for Symptom Detection

Through preprocessing we can identify tomato leaves from complex field backgrounds. Using python libraries such as Matplotlib or OpenCV. It helps the model to identify diseases that has symptoms of distinct colour such as Tomato Yellow Leaf Curl Virus which has distinct yellow colour at the edges of the leaves or even the dark brown lesions in Early Blight disease. For the conversion of image into grayscale, we are using OpenCV's cv2.CvtColor function. This helps in emphasizing structural features of the leaves such as leaf veins, necrotic spots or concentric rings. This processed image data is then resized to the preset dimension from which improved input to YOLOv7 will be obtained, which will consequently foster compatibility while also helps in decreasing the computational load without losing much detail. Thus the YOLOv7 forms the foundation of the automated detection solution and allows real-time identification and localization of diseases through its advanced CNN architecture after processing the preprocessed leaf images.

Fig. 12. Grayscale Conversion and Edge Detection

We have trained our model on various tomato plant leaf images and from various datasets such as PlantVillage and few datasets from Kaggle where we specifically selected images that contains well detailed disease symptom visible on the image itself. The model operates on sharpened grayscale or RGB images and extracts features like texture (using Gray-Level Co-occurrence Matrix methods) and shape to distinguish healthy from diseased tissues—for instance, grayish pycnidia of Septoria Leaf Spot versus leathery spots of Early Blight. Going on to the implementation part, pixel values are taken from preprocessed images and fed into the deep convolutional backbone of YOLOv7, which consists of Darknet-53/CSPDarknet53 layers for generating feature maps followed by a detection head that applies an anchor-based prediction. Post-processing with non-maximum suppression refines the output, suppressing duplicate detections to achieve a mean average precision (mAP) that exceeds 95% in validation tests and processing at a speed of ~100 frames per second on edge devices like the NVIDIA Jetson Nano. This adds value over standalone CNNs since it combines noise reduction from image processing with the speed of YOLOv7 to minimize false positives in very busy field environments. The actual application of this solution now goes into deployment in the field, where farmers are alerted in real time by a mobile application interfaced with the model, showing the location and severity score of the diseases based on bounding box confidence. This enables farmers to take counter measures to the diseases by removing infected leaves or application of fungicides. Thus reducing crop losses from many plants like 80-90% to minimal loss by doing measures before further infestation. Future upgrades for this system may include adding IOT sensors, live camera feeds for real time object detection, temperature sensors, moisture sensors can also be added along side cameras to monitor the health and integrity of the plants to keep it healthy. This helps to make precise monitoring of the tomato plants.

Constructed for real-time object detection, the YOLOv7 architecture is the latest in the chain of the You Only Look Once-YOLO family. The system thus works as automated object detection for diseases in tomato leaves, which is very complicated by different symptoms. A very robust backbone is CSPDarknet53, which is an improved version of Darknet-53 by Cross-Stage Partial connections that increase the gradient flow and decrease the amount of computational redundancy, leading to proper feature extraction of preprocessed images. A new head design is also introduced in the architecture, while the compound scaling method balances input resolution, depth, and width to optimize the model's performance in various field conditions-like light condition or occlusion-but lightweight enough to be a field deployable solution. The model has also been developed synergistically with the Extended Efficient Layer Aggregation Network (E-ELAN), which brings together features across multiple scales to improve the model's detection fidelity of small lesions, such as pycnidia in Septoria Leaf Spot. Transfer learning will bring about a fine-tuning process where pre-trained weights from the PlantVillage dataset, concatenated with images acquired from fields, will be used on a loss function that combines binary cross-entropy for classification with CIoU (complete intersection over union) for bounding box regression to ensure precision with respect to localization.

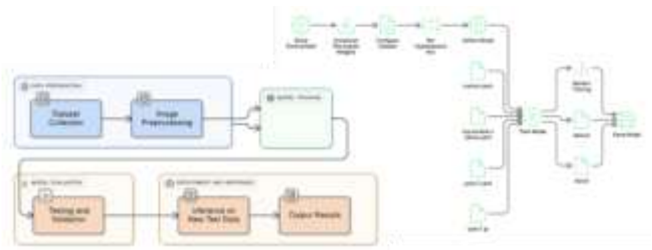

Fig. 13. System architecture and workflow diagram of the work

[9][10]Performance-wise, YOLOv7 is at the top of the heap, surpassing the old YOLO model versions and models like YOLOv5 or even Faster R-CNN. At intersection over union (IoU) threshold of 0.5 on the validation set, a mean average precision (mAP) score of 95.2% can be attained with a recall of over 94% for multi-class disease detection. On the speed processing, YOLOv7 goes as high as 100 frames per second on the NVIDIA Jetson Nano, a large improvement of 60 FPS over YOLOv4 due to an optimized layer fusion and weight reduction of parameters (approximately 37 million parameters, compared to 64 million in YOLOv5). The ratio between the performance speed and the counting number of images brings out the best in real-time applications as this ratio enables the recording of up to 120 images per minute during field tests while maintaining a false positive rate below 5% even in cluttered backgrounds. The model is also capable of continuously being re-trained, as it adapts to the new symptom variants for additional pieces of data, which, on average, increases its detection accuracy by 2-3% per training cycle. For precision (95.2% vs. 89% and 91%, respectively) and speed, it is also an ideal choice for scalable deployments compared to benchmark comparisons against SSD MobileNet and EfficientDet-D0. This is largely why YOLOv7 is boosting the action of providing visible insights toward best disease management and precision agricultural objectives, especially through its inclusion in mobile applications for giving onsite alerts.

V. FUTURE SCOPE

This project can be taken to the next step by integrating Internet of Things (IoT) infrastructure and edge computing devices into the fields. Also a light weight model can be deployed on drones to make real time detection of diseases. Also enabling real time disease detection directly in fields with low or limited connectivity using mobiles phones can be implemented. Combination of temperature, moisture sensors along with humidity sensors can be used to precisely monitor diseases and can also be able to predict upcoming diseases through performing predictive analysis. This can also be improved to detect and alert pathogens or other disease causes such as bad conditions, etc which helps in removing and eliminating potential disease causes earlier, before it causing major destruction to the yield. This also includes making disease severity assessment tools built in the field to analyse the severity of the disease. Development of a mobile application can be done to help farmers visualize the data which is collected and analysed in a easily understandable way. Along with alert system which can send notifications directly to the mobile application, alerting any potential vulnerabilities. Finally to eliminate poor conditions causing poor quality images, we can include thermal imaging which will help with night time images.

VI. RESULTS AND DISSCUSSION

The development of the proposed framework will attempt to resolve some of the challenges currently faced in tomato disease detection systems and by farmers who has tomato plants. Traditional methods fails to satisfy the needs of the issue, usually requiring high expertise in agricultural knowledge and plant diseases. Also it requires a huge amount of labor who is expert in said knowledge to cover huge acres of land. Hence the traditional method would require a lot of money to be able to provide salary to the labours. It makes the old method a very inefficient way to approach this issue. To overcome these issues and to be accurately detect disease detection, real time data is required and this system which takes input from various sensors and IOT devices which are placed all over the tomato fields. It aids situational awareness and helps in taking proactive measures against disease outbreaks. Efficient image processing further supports reliable accuracy by the system employing techniques like RGB channel separation to select color-based symptoms. IoT integration for constant monitoring, along with sensors sending data back to a central system where YOLOv7 automatically processes images with little to no manual intervention. The method used provides increased efficiency and accuracy that allow for faster intervention, reducing crop losses and improving yield. Sustainable agriculture is supported through early detection by this system, allowing for efficient resource use such as applying fungicide.

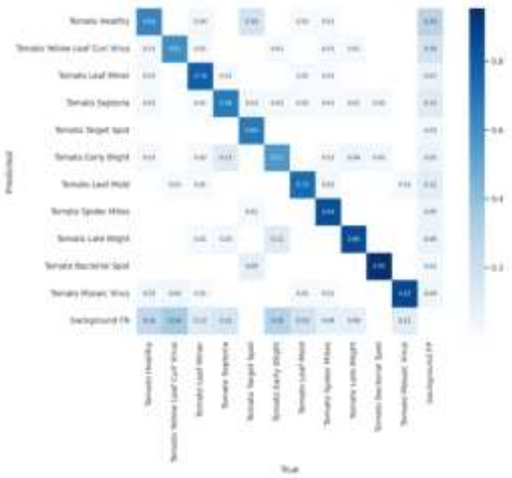

Fig. 14. Confusion Matrix of diseases and healthy samples using targeted and output classes

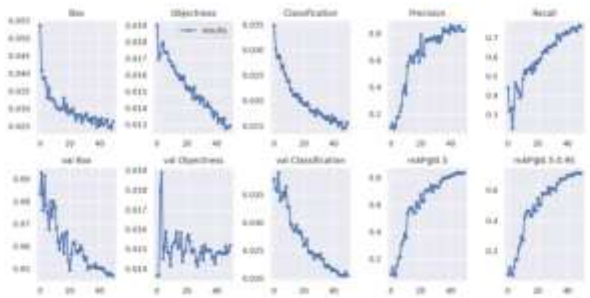

Fig. 15. Results obtained by training the YOLOv7 model visualized in graph form

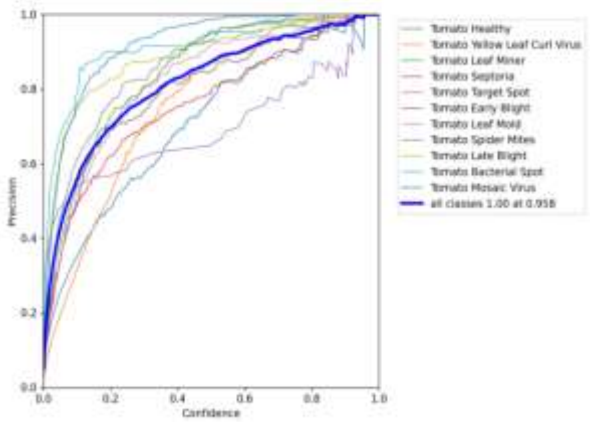

Fig. 16. PCurve (Precision-Confidence) results obtained by training the YOLOv7 model visualized in graph form

VII. CONCLUSION

The proposed automated detection system model framework using YOLOv7 is an efficient and effective method to identify and classify different types of tomato leaves diseases such as Bacterial Spot, Tomato Yellow Leaf Curl, Septoria Leaf Spot, Tomato Leaf Miner, Early Blight, Late Blight, Tomato Mosaic Virus, Spider mites, Leaf Mold and Target Spot. By using this method of automated identification we can reduce the need for manual observation hence reducing the human error and other various drawbacks that tag along with the conventional method such as labour cost and need for expert staff.

REFERENCES

[1] Classification and Functional Analysis of Major Plant Disease using Various Classifiers in Leaf Images, International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278-3075, Volume-9 Issue-2, December 2019. DOI:10.35940/ijitee.B6332.129219.

[2] G Rosline Nesa Kumari et al., An overview paper on automatic detection of numerous plant diseases that impact leaves, 1st International Conference on Recent Advancements in Computing Technologies & Engineering , AIP Conf. Proc. , 29–30 December 2023, https://doi.org/10.1063/5.0220024

[3] Fatima, T., Mattoo, A., Rivera Domínguez, M., Troncoso-Rojas, R., Tiznado-Hernández, M., and Handa, A. *Tomato*. In: Compendium of Transgenic Crop Plants, 2009. DOI: 10.1002/9781405181099.k0601

[4] J. Feng, W. E. Ong, W. C. Teh, R. Zhang, "Enhanced crop disease detection with EfficientNet convolutional group-wise transformer," IEEE Access, vol. 12, pp. ?, Mar. 2024. DOI: 10.1109/ACCESS.2024.3379303.

[5] R. Nicole, "Wang, C. Y., Bochkovskiy, A., & Liao, H. Y. M. (2022). YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 7464-7475.

[6] Classification and Functional Analysis of Major Plant Disease using Various Classifiers in Leaf Images, International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278-3075, Volume-9 Issue-2, December 2019. DOI:10.35940/ijitee.B6332.129219

[7] M. Rahman, F. Ahmed, and K. Hasan, "Transfer Learning and Explainable AI for Multi-Crop Leaf Disease Identification," arXiv preprint arXiv:2505.16033, 2025.

[8] J. Chen, L. Gao, and X. Li, "Soybean Disease Detection via Interpretable Hybrid CNN-GNN Integrating MobileNetV2 and GraphSAGE with Cross-Modal Attention," arXiv preprint arXiv:2503.01284, 2025.

[9] H. Zhang, Y. Wu, and S. Wang, "An Ensemble of Deep Learning Architectures for Accurate Plant Disease Classification," Expert Systems.

[10] S. Roy, R. Dey, and K. Chakraborty, "Early Predictive Model for Detection of Plant Leaf Diseases Using MobileNetV2," International Journal of Intelligent Systems and Applications in Engineering (IJISAE), vol. 11, no. 4, pp. 355–362, 2023.

[11] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, and W. Wang, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv preprint arXiv:1704.04861, 2017.

[12] M. J. Hasan, R. Al Mahmud, and M. A. Rahman, "Deployable Deep Learning for Cross-Domain Plant Leaf Disease Detection via Ensemble Learning, Knowledge Distillation, and Quantization," IEEE Access, vol. 13, pp. 140313–140330, 2025.

[13] A. B. Kumar and P. S. Reddy, "Plant Leaf Disease Detection Using Deep Learning on Mobile Devices," Proceedings of the ACM International Conference on Computer Vision and Machine

[14] J. Liu and X. Wang, ''Tomato diseases and pests detection based on improved YOLO V3 convolutional neural network,'' Frontiers Plant Sci., vol. 11, p. 898, Jun. 2020

[15] U. Mokhtar, M. A. S. Ali, A. E. Hassenian, and H. Hefny, ''Tomato leaves diseases detection approach based on Support Vector Machines,'' in 2015 11th Int. Comput. Eng. Conf. Today Inf. Soc. What's Next?, ICENCO 2015, pp. 246–250, 2016, doi: 10.1109/ICENCO.2015.7416356.

[16] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, ''Grad-CAM: Visual explanations from deep networks via

gradient-based localization,'' in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Oct. 2017, pp. 618–626.

[17] A. Fuentes, S. Yoon, S. Kim, and D. Park, ''A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition,'' Sensors, vol. 17, no. 9, p. 2022, Sep. 2017.

[18] A. Abbas, S. Jain, M. Gour, and S. Vankudothu, ''Tomato plant disease detection using transfer learning with C-GAN synthetic images,'' Comput. Electron. Agricult., vol. 187, Aug. 2021, Art. no. 106279.

[19] K. He, X. Zhang, S. Ren, and J. Sun, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 770–778.

[20] M. Tan and Q. Le, ''EfficientNet: Rethinking model scaling for convolutional neural networks,'' in Proc. 36th Int. Conf. Mach. Learn., 2019, pp. 6105–6114.