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Original Article

Survey on Disease Identification and Severity Level Estimation on Plant

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Abstract: *The most nutritive crop that is being cultivated across the globe is the tomato plant. Moreover, it has a vital impact on the growth of the agricultural economy in terms of cultivation and export levels Plants not only contains protein, but also has pharmacological properties that safeguard the people from conditions like "high blood pressure, hepatitis, gingival bleeding", etc. Nowadays, they are utilized in a large- scale, and as a consequence of this, the market for plants is also getting increased. Statistics reveal that the small producers produce more than 80 percent of plant and therefore, the economic losses are more than 50 percent due to the insects and pathogens. The primary issues affecting the plants development are pathogens and insect pests, so researching the detection of crop diseases is especially important. The management of plants diseases is indeed a difficult process that requires constant care during the growing season and is responsible for the substantial fraction of overall production level. Earlier identification could significantly minimize the treatment costs, mitigate the severity of chemical contaminants, and alleviate the chances of yield loss. Present methods of disease diagnosis are restricted in terms of time required for qualified technicians to physically identify and evaluate the pathogens, exacerbated by the number of plants in commercial greenhouses and the small scale of indications at the early stage of disease. Usually, the cost and complexity involved in disease detection restricts the outbreak exploration to an occasional cycle or limited sampling. Molecular processing, spectroscopy, and examination of volatile organic compounds have been used in the studies of the automatic detection processes. Though, they are costly and inefficient to implement on a real - time operating scale.*

Keywords: *Automatic Detection Processes. Disease Detection, Real - Time Operating Scale.*

I. INTRODUCTION

Managing plant diseases is a difficult operation that necessitates constant attention throughout the crop cycle and represents a sizeable portion of overall production expenses. The expense of treatment, the environmental impact of chemical inputs, and the danger of yield loss can all be reduced with earlier diagnosis. Because of the number of plants found in commercial greenhouses and the tiny size of early disease symptoms, current disease detection approaches are limited by the time needed for experienced laborers to physically discover and diagnose disease. Due to the cost and time involved, disease scouting is often restricted to sporadic schedules or sparse sampling, which can miss early localized symptoms and significantly affect the severity of an outbreak. the study of automatic detection.

The management of plants diseases is indeed a difficult process that requires constant care during the growing season and is responsible for the substantial fraction of overall production level earlier identification could significantly minimize the treatment costs, mitigate the severity of chemical contaminants, and alleviate the chances of yield loss. Present methods of disease diagnosis are restricted in terms of time required for qualified technicians to physically identify and evaluate the pathogens, exacerbated by the number of plants in commercial greenhouses and the small scale of indications at the early stage of disease Usually, the cost and complexity involved in disease detection restricts the outbreak exploration to an occasional cycle or limited sampling. Molecular processing, spectroscopy, and examination of volatile organic compounds have been used in the studies of the automatic detection processes. Though, they are costly and inefficient to implement on a real - time operating scale The potential of machine learning techniques to identify the existence of plant diseases via deep convolutional neural network models has been demonstrated by experiments with recognizable features imaged by traditional RGB cameras.

It is a difficult process that necessitates ongoing care throughout the crop cycle and contributes significantly to overall production expenses. Early diagnosis can cut treatment costs, lessen the impact of chemical inputs on the environment, and lessen the chance of crop loss. Due to the volume of plants found in commercial greenhouses and the small size of early disease symptoms, current disease detection techniques are limited by the time needed for skilled laborers to manually locate and assess disease. Due to the cost and time involved, disease scouting is often restricted to sporadic schedules or sparse sampling, which can miss early localized symptoms and significantly affect the severity of an outbreak. Molecular analysis, spectroscopy, and analysis of volatile organic molecules have all been investigated as automated detection techniques but are expensive and difficult to use at commercial operational sizes. Studies employing visible characteristics captured by traditional RGB cameras have demonstrated that deep convolutional neural network models can be used by machine learning systems to detect the presence of known plant diseases. Prior to the release of the Plant Village dataset, which contains thousands of images of plant leaf disease from twelve crop species, including nine plant diseases, deep learning models typically needed only small plant disease datasets to make accurate generalizations. Previous deep learning models that were trained on the Plant Village dataset were quite accurate at identifying previously observed illness symptoms. Studies with smaller datasets, including fewer Plant Village photos, also shown high accuracy rates. However, smaller datasets are anticipated to produce models with lower performance for datasets with classes that have similar visual appearances, such as those of various plant leaf diseases.

II. RELATED WORK

In order to improve the accuracy of identifying plant leaf diseases, Q. Wu et al. [1] created a novel approach for DA utilising GANs in 2021. In order to improve the recognition accuracy of plant leaf diseases, a new technique of data augmentation utilising GANs was developed in this study. Due to the generated images enhanced by DCGAN and the original images used as Google Net input, this model had a top-1 average recognition accuracy of 94.33 percent.

Three networks—the location network, the input network, and the LFC-Net classification network—make up a new paradigm that Yang et al. [2] presented in 2020. In addition, they have devised a self-supervision system that can quickly identify certain sections of an image that include detailed plants without the need for user annotation. Additionally, they have created a novel learning strategy that emphasises both comprehensibility and continuity within image groups. The model's position framework first identifies the perceptive areas in the image of the plants, and then, with the help of the Feedback network, the iterations were optimised.

A more advanced Faster RCNN was proposed by Joshi et al. [3] in 2020 with the aim of diagnosing stable plant leaves and four diseases: "powdery mildew, blight, leaf mould fungus, and ToMV." This method was offered as a way to improve the model's accuracy for pinpointing the location of infected leaves and identifying crop disease leaves. Second, they employed a depth residual network to replace VGG16 for extracting features so that they could obtain more detailed illness features. The k-means clustering technique was then applied to group the bounding boxes. The testing findings showed that the proposed upgraded system had more rapid and more accurate detection of the leaf illness than the original Faster RCNN.

Gonzalez-Huitron et al.'s [4] novel robotic detection method for PM and TSWV identification was released in 2021. They have proposed a robotic detection method for the simultaneous detection of two significant hazards to greenhouse bell peppers: PM and TSWV. The technology uses a manipulator, which makes it simple to enter different settings for the detection of the diseases indicated above. Additionally, a number of detection algorithms centred on PCA and the CV are developed. According to test results, the framework successfully diagnosed the disease and attained the necessary detection stance for PM, while it was challenging to get the necessary detection pose for TSWV. The solution to this conundrum was meant to be increased manipulator work-volume. "TSWV, PCA- based classification with leaf vein elimination" had the highest classification accuracy.

A contemporary computer vision framework to recognise various diseases, particularly the plants disease, was introduced in 2021 by Rizwana et al. [5]. This research introduces a new computer vision framework to automatically detect various diseases, diagnose previously unrecognised diseases, and forecast per-leaf intensity. The PlantVillage plants dataset's 9 plant disease forms were used for training and testing, and it was shown whether or not different tree attributes affected the detection of illnesses. A new strategy for greenhouse plants was developed in 2020 by Alizadeh-Moghaddam et al. [6] using a real-time decision support system to identify the monitoring phase, detect climate sensor failures, control stage, manage climate variables at set-points, and strategic stage, identify crop-affecting diseases, and adjust climate variables to mitigate harm as necessary. The

DSS was introduced by adding a "real-time rule-based tool" to the control framework. According to experimental results, the framework has increased the effectiveness of climate regulation, ensuring that there are resources available to eradicate diseases that are challenging to remove.

Rashid [7] introduced two separate profound ways to identify the type of plant leaf infection in 2020. The first architecture also uses residual learning to learn the key grouping features. In the second design, the attention mechanism is added on top of the remaining deep network.

Kumar et al.'s [8] new paradigm for identifying plant leaf disease was proposed in 2020. The authors suggest a fresh approach for identifying plant leaf disease. In the beginning, the BWTR enhanced the quality of the image by removing "noise points and edge points," and this preserved crucial texture detail. Artificial Bee Colony (ABCK) was used to isolate plant leaves from the background using KSW. Eventually, the B-ARNet architecture was also utilised to identify the frames.
To determine whether different tree characteristics can identify the diseases, C. Zhou, S. et al. [9] introduced a Plants Leaf Disease Identification by Restructured Deep Residual Dense Network in 2021.

DCGAN-Based Data Augmentation for Plants Leaf Disease Identification is carried out in 2020 by Q. Wu, Y. Chen et al. [10]. In the paper, use various optimisation and severity calculation algorithms. To define the types of diseases, G. Yang et al. [11] introduced Self-Supervised Collaborative Multi-Network architecture in 2020. They also used Fine-Grained Visual Categorization of Plant Diseases. By utilising early detection and preventive systems, Y. Zhang et al. [12] proposed Deep Learning-Based Object Detection Techniques for Plant Disease Improvement in 2020.

Powdery mildew (PM) and Plants Spotted Wilt Virus (TSWV), two main diseases to greenhouse bell peppers, were merged into one robotic detection system in 2016 by N. Schor et al. [13]. While the accuracy of the CV methods was also high (85% and 87%), PCA-based classification with leaf vein removal had the highest classification accuracy (90%). While leaf condition classification accuracy was low (64.3%) because it was based on the upper side of the leaf while disease symptoms begin on its lower side, PCA-based pixel-level classification for PM had a high accuracy rate of 95.2%.

In 2021, Sangeeta, et al. [14] found a novel method to increase the accumulation of ToLCGanV when homologous ToLCGanB was present, but ToLCMumB had no effect on the amount of ToLCMumV in the agro-inoculated plants. The findings show that the cloned viruses create disease complexes in India that have the capacity to overcome virus resistance. Investigating the spread of these disease complexes to important plant-growing regions in the nation is therefore necessary.

2020 saw the introduction of field studies by Ting Shen, et al. [15] that shown that BOF-G33 greatly reduced the incidence of plants wilt; the disease biocontrol efficiency was 64.4%. Furthermore, the BOF-G33 application significantly decreased the pathogenic R. solanacearum populations and increased the amount of beneficial indigenous flora in the rhizosphere soil, which may have been the primary factors in limiting the disease. In conclusion, this study shown that Streptomyces microflavus G33 bioorganic fertiliser is a viable biocontrol agent for preventing bacterial plant disease.

Research on seed priming with mycogenic selenium nanoparticles (SeNPs) for inducing resistance to plants' late blight disease has been published by Shreya M., et al. [16] in 2020. Additionally, it seeks to comprehend how SeNPs affect cellular, biochemical, and transcriptomic defence mechanisms. In comparison to control plants, plants primed with bioactive SeNPs showed improved plant growth metrics.

In 2021, Victor Gonzalez-Huitron.,et al. [17] have suggested a precision irrigation technique based on discrete time model predictive control (MPC). To reduce the computational complexity of the proposed techniques, the use of Laguerre functions to approximate the control horizon is proposed. Using simulations in MATLAB, the results shows that the proposed technique can approximate the behavior of a discrete linear quadratic regulator with sufficientaccuracy.

Bangle rhizome extract was first introduced in 2021 by Humaira Rizwana et al. [18] It is postulated that among the benefits of bangle rhizome extract is its ability to prevent and reduce symptoms that occur in Covid-19, but preclinical studies and clinical studies are required to prove this postulate.

In 2020, Giti Alizadeh-Moghaddam., et al. [19] proposed that it is possible to distinguish resistant from susceptible plant genotypes to the early blight disease by using both genetic diversity and enzymatic diversity as markers.The Un-weighted Pair Group Method with Arithmetic Mean (UPGMA) analysis separated the plant genotypes into five clusters and revealed a striking connection between resistance level and molecular classification pattern.

The three active endophytic fungal isolates may serve as a foundation for the discovery of novel bioactive chemicals and the efficient biocontrol of plant bacterial spot, according to Tavga Sulaiman Rashid et al. in 2020 [20].

S. Dhakshina Kumar, et al. [21] examined the system's performance in 2020 and calculated statistical parameters such accuracy, specificity, sensitivity, error rate, and F1 score. And a comparison analysis is done to show that the method is effective in predicting plant diseases when compared to other traditional methods like Probabilistic Neural Network (PNN), K-Nearest Neighbour (K-NN), and Back Propagation Artificial Neural Network (BPANN).

The yeast that expresses flagellin on the cell surface has been shown by Shixue Zhao et al. to considerably increase disease resistance against B. cinerea in plant wounds as of 2019 [22]. The yeast strain producing flagellin significantly up-regulated the genes for salicylic acid and jasmonic acid production as well as plant defence in plants with wounds.When the yeast strain was applied, it greatly increased the production of superoxide radicals in tobacco leaves and plant fruit. These results suggest that increasing the biocontrol effectiveness of antagonist yeast against disease in postharvest fruit may be accomplished by expressing flagellin at yeast cell surface.

The impact of this treatment on the soil microbiome as well as the underlying mechanism causing disease suppression were assessed using high-throughput sequencing in 2019. In 2019, Xuhui Deng et al. [23] proposed based on fumigation using ammonium bicarbonate along with organic amendment to reduce disease severity. Despite the fact that R. solanacearum is present in significant concentrations in all treatments' bulk and rhizosphere soil, the system demonstrated that this combined approach successfully suppresses plant bacterial wilt disease.

The strength of the segmentation used in Saiqa Khan et al.'s [24] system, which was developed in 2020, is measured by the True Positive Rate (TPR), False Positive Rate (FPR), False Negative Rate (FNR), Positive Prediction Value (PPV), False Discovery Rate (FDR), Accuracy, and F1 score.

In 2019, G Brammya et al. [25] built a system that uses 3 engineering applications and 39 benchmark functions. Additionally, a specific application is used to demonstrate the effectiveness of the algorithm in classification by integrating NN in DHOA (DHOA-NN). The performance comparison with other optimisation algorithms and the algorithm's testing in real-time engineering applications demonstrate the DHOA algorithm's superiority.

III. CONCLUSION

This study focuses on a survey of several disease classification methods for plant leaf disease detection as well as an algorithm for picture segmentation that can be applied to both the automatic and manual detection and classification of plant leaf diseases. The image in the suggested architecture will be de-noised and segmented. The Convolutional Neural Network (CNN) used in the detection phase to identify diseases will receive features as input. Furthermore, a new hybrid model will be used to fine-tune CNN's weight in order to improve the disease classification accuracy. Additionally, the severity estimation will be used to determine the final prediction results.

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