Recent Research Status on Disease Identification in 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

Plants disease management is a challenging process, requiring continual attention throughout the crop cycle and accounts for a significant fraction of total production costs earlier detection can help reduce the cost of treatment, lower the environmental impact of chemical inputs, and mitigate risks of yield loss. Current disease detection techniques are limited by the time required for expert laborer to manually locate and assess disease, which is complicated by the volume of plants found in commercial greenhouses and the small size of disease symptoms at their earliest stages. The expense and time required typically limits disease scouting to an infrequent schedule or sparse sampling, which can miss early localized symptoms and have a significant impact on the severity of an outbreak. Investigations into automated detection methods have included molecular analysis, spectroscopy, and analysis of volatile organic compounds but are expensive and impractical to apply at commercial operating scales [5].

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 challenging process, requiring continual attention throughout the crop cycle and accounts for a significant fraction of total production costs. Earlier detection can help reduce the cost of treatment, lower the environmental impact of chemical inputs, and mitigate risks of yield loss. Current disease detection techniques are limited by the time required for expert laborers to manually locate and assess disease, which is complicated by the volume of plants found in commercial greenhouses

II. RELATED WORK

In 2021, Q. Wu et al. [1] have developed a novel system for DA through GANs for leaf disease identification to increase the recognition accuracy of plants leaf diseases. In this article, a new system of data augmentation through GANs was proposed to increase the recognition accuracy of plants leaf diseases. This model had achieved a top-1 average recognition accuracy of 94.33 percent resulting from the generated images augmented by DCGAN and original images as GoogLeNet input.

In 2020, Yang et al. [2] have introduced a new paradigm consisting of three networks, namely the position network, the input network and the LFC-Net classification network. Simultaneously, they have introduced a self-supervision system that can efficiently detect detailed plants image regions without a need for manual annotation. In addition, they have developed a novel learning approach focused on considering the continuity between image group as well as the comprehensibility. The model position framework initially recognizes the insightful regions throughout the plants image, and then under the supervision of the Feedback network, the iterations were optimized.

In 2020, Joshi et al. [3] have suggested an enhanced Faster RCNN with the intention of diagnosing stable plants leaves and four diseases: “powdery mildew, blight, leaf mold fungus and ToMV”. This technique was suggested to boost the models precision for crop disease leaves identification and the position of diseased leaves localization. Second, to substitute VGG16 for extracting features, they have used a depth residual network, so that they were able to acquire deeper disease features. Finally, to cluster the bounding boxes, the k-means clustering algorithm was being used. The experimental results have demonstrated that the proposed enhanced system had achieved better precision and a quicker level of detection than the initial Faster RCNN for detecting the leaf disease.

In 2021, Gonzalez-Huitron et al. [4] have introduced a new robotic detection approach for PM and TSWV identification. For the simultaneous identification of two major threats to greenhouse bell peppers, they have presented a robotic detection system: PM and TSWV. The technology relies on a manipulator, which makes it easy to enter several configurations for the identification of aforementioned diseases. Moreover, centered on PCA and the CV, several detection algorithms are created. Test results established that the framework had detected the disease successfully and had achieved the detection pose needed for PM, but it was difficult to reach the detection pose of TSWV. This dilemma was supposed to be overcome by improved manipulator work- volume. The highest classification accuracy was achieved for “TSWV, PCA- based classification with leaf vein elimination”,

In 2021, Rizwana et al. [5] have introduced a modern computer vision framework to recognize numerous diseases, especially the plants disease. A modern computer vision framework was introduced in this paper to automatically identify numerous diseases, diagnose previously unseen diseases, and predict per-leaf intensity. Training process and testing used multiple updated variants of the 9 plants disease forms in the PlantVillage plants dataset and demonstrated whether different tree characteristics influence the identification of diseases.

In 2020, Alizadeh-Moghaddam et al. [6] have developed a new approach for greenhouse plantses using the real-time decision support system to identify the monitoring phase, detects climate sensor faults, the control stage manages climate variables at set- points, and the strategic stage identifies crop-affecting diseases and adjusts climate variables to mitigate harm accordingly. By incorporating a “real-time rule-based tool” into the control structure, the DSS was introduced. Experimental findings have indicated that the framework has improved the efficacy of climate regulation thereby ensuring resources to eliminate difficult-to- eradicate diseases.

In 2020, Rashid [7] have introduced the two distinct profound mechanisms towards determining the form of plants leaf infection. Further, to learn the essential characteristics of grouping, the very first architecture applies residual learning. On top of the remaining deep network, the second design introduces the attention mechanism.

In 2020, Kumar et al. [8] have suggested a new framework for the identification of plants leaf disease. The authors have recommended a new framework for the identification of plants leaf disease. Initially, the BWTR have improved the image quality by removing “noise points and edge points”, and thereby preserves essential texture detail. Using KSW, plants leaves were isolated from the background with Artificial Bee Colony (ABCK). Eventually, the framework of the B-ARNet was also used to recognize the frames.

In 2021, C. Zhou, S. et al. [9] have introduced a Plants Leaf Disease Identification by Restructured Deep Residual Dense Network whether different tree characteristics identify the diseases.

In 2020, Q. Wu, Y. Chen et al. [10] have DCGAN-Based Data Augmentation for Plants Leaf Disease Identification is done. Use different optimization and severity calculation algorithm in paper.

In 2020, G. Yang et al. [11] have introduced Self-Supervised Collaborative Multi-Network design and use of Fine-Grained Visual Categorization of Plants Diseases to clarify the type of diseases.

In 2020, Y. Zhang et al. [12] have suggested Deep Learning-Based Object Detection methods for Improvement for Plants Disease by using early prevention detections systems.

In 2016, N. Schor et al. [13] have developed a new approach for robotic detection system for combined detection of two major threats of greenhouse bell peppers: Powdery mildew (PM) and Plants spotted wilt virus (TSWV). PCA-based classification with leaf vein removal, achieved the highest classification accuracy (90%) while the accuracy of the CV methods was also high (85% and 87%). For PM, PCA-based pixel-level classification was high (95.2%) while leaf condition classification accuracy was low (64.3%) since it was determined based on the upper side of the leaf while disease symptoms start on its lower side.

In 2021, Sangeeta,et al. [14] have developed a new approach to enhanced accumulation of ToLCGanV was detected in the presence of cognate ToLCGanB, however ToLCMumB did not influence the level of ToLCMumV in the agro-inoculated plants plants. In results indicate that the cloned viruses form potential virus resistance breaking disease complexes in India. This necessitates investigating the spread of these disease complexes to major plants growing regions in the country.

In 2020, Ting Shen,et al. [15] have introduced field experiments that showed that BOF-G33 significantly decreased the incidence of plants wilt; the disease biocontrol efficiency was 64.4%. In addition, application of the BOF-G33 significantly reduced the pathogenic R. solanacearum populations and increased the abundance of beneficial indigenous flora in the rhizosphere soil, which might have been the key factors in constraining the disease. In conclusion, this study showed that bioorganic fertilizer with Streptomyces microflavus G33 is a potential biocontrol agent for controlling plants bacterial disease.

In 2020, Shreya M.,et al. [16] have introduced work seed priming with mycogenic selenium nanoparticles (SeNPs) for elicitation of resistance against plants late blight disease is investigated. It also aims to understand the defense responses triggered by SeNPs at cellular, biochemical and transcriptomic levels. Enhanced plant growth parameters were observed in bioactive SeNPs-primed plants plants as compared to control plants.

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.

In 2021, Humaira Rizwana.,et al. [18] have introduced bangle rhizome extract has dozens of nutritious substances and has multifunctional activities, and it can be postulated that among the benefits of bangle rhizome extract it is able to prevent and reduce symptoms that occur in Covid- 19, and preclinical studies and clinical studies are needed to prove this postulate.

In 2020, Giti Alizadeh-Moghaddam.,et al. [19] have suggested that using both genetic diversity and enzymatic diversity as markers, it is possible to discriminate resistant from susceptible plants genotypes to early blight disease.The Plants genotypes were divided into five clusters in Un-weighted Pair Group Method with Arithmetic Mean (UPGMA) analysis, showing a considerable similarity between resistance level and molecular classificationpattern.

In 2020, Tavga Sulaiman Rashid.,et al. [20] have suggested that the three active endophytic fungi isolates provide a basis for the identification of new bioactive compounds, and for the effective biocontrol of bacterial spot of plants.

In 2020, S. Dhakshina Kumar.,et al. [21] have evaluated the performance of the system some statistical parameter such as accuracy, specificity, sensitivity, error rate, F1 score are calculated. And to prove that the method functions effectively in disease prediction of plants when compared to other conventional method such as Probabilistic Neural Network (PNN), K- Nearest Neighbour (K-NN) and Back Propagation Artificial Neural Network (BPANN) a comparison analysis is performed.

In 2019, Shixue Zhao et al. [22] have showed that the yeast expressing flagellin at cell surface could significantly induce disease resistance against B. cinerea in plants wounds. The genes involved in biosynthesis of salicylic acid and jasmonic acid, and plant defense were markedly up-regulated in plants wounds by the yeast strain expressing flagellin.application of the yeast strain significantly induced the superoxide radical generation in tobacco leaves and plants fruit. These findings suggest that expressing flagellin at yeast cell surface may be an effective strategy to increase the biocontrol efficiency of antagonist yeast against disease in postharvest fruit.

In 2019, Xuhui Deng et al. [23] have suggested based on fumigation using ammonium bicarbonate along with organic amendment to reduce disease severity, and the impact of this treatment on the soil microbiome as well as the underlying mechanism leading to disease suppression were evaluated using high-throughput sequencing. System showed that this combined strategy effectively controls plants bacterial wilt disease despite the high abundance of R. solanacearum in both the bulk and rhizosphere soil in all treatments.

In 2020, Saiqa Khan et al. [24] have developed system lies in the fact that the segmentation is effective for all the varied datasets and it is evaluated by 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] have developed system is carried out with 39 benchmark functions and 3 engineering applications. Moreover, a specific application is exploited by integrating NN in DHOA (DHOA-NN), to showed the efficiency of the algorithm in the classification. The algorithm experimented in real-time engineering applications and the performance comparison with the existing optimization algorithms proves the superiority of the DHOA algorithm.

III.PROPOSED WORK

Tomato production is severely impaired by the outbreak of tomato diseases and pests in various areas. It can lead to yield loss or even crop failure if the monitoring is not timely. The solution to reduce the yield loss and decrease the application of pesticides is to grow pollution-free crops by avoiding diseases and pests. Early detection and elimination of outbreaks and pests is also quite significant. The conventional method of automated disease diagnosis and insect pests relies solely on the knowledge of the grower's assessment or asking for advice from experts. With the ongoing advancement of the Internet, the use of computer technologies brings new approaches and ideas for detecting crop diseases and insect pests. Using appropriate technology for computer vision can increase the quality of image recognition, decrease costs, and improve the accuracy of recognition. Therefore, a lot of study has been conducted by experts and academics at home and abroad, of which deep learning has been the research subject. The use of deep learning in the detection of crop diseases and pests will significantly decrease the burden and lessen the recognition time. The largest features of deep learning are dynamic network structure and big data samples. Good technological support for image recognition is provided by the advent of deep learning technologies. Among them, a common model of deep learning is CNN. The CNN-based method of detecting diseases and pests will automatically extract the attributes in the image, which in conventional methods overcomes the subjectivity and restriction of artificial feature extraction. The end-to-end architecture optimizes the method of identification and addresses the issues that the manually built feature extractor does not get the description of the feature nearest to the object's natural attribute. Not only does it save time and resources depending on the implementation of CNN target identification, but it can also perform real-time judgements. However, the judgement becomes effective and precise only for small datasets, when it comes for large dataset, it becomes complex and inappropriate to predict the results. This scenario is due to the lagging of proper information, as the system must feed with the relevant information that impacts for the disease formation.

In this research work a new tomato leaf disease prediction will be introduced by following 5 major phases: (a) pre-processing, (b) image segmentation, feature extraction, classification and severity estimation. Fig.1 shows the architecture of the proposed work. Initially, the collected raw image will be de-noised in the pre-processing phase. Then, these pre-processed images will be segmented via a modified watershed algorithm. Subsequently, the most relevant features like the "texture feature, color feature, disease area and pixel features" will be extracted. These features will be fed as input to the detection phase that use Convolutional Neural network (CNN) for disease identification. Further, to enhance the classification accuracy of the disease, the weight of CNN will be fine-tuned via a new hybrid model. Moreover, the final prediction results will be based on the estimation of severity. The proposed hybrid model will be the conceptual blending of the standard Deer Hunting Optimization Algorithm (DHOA) [25] and Whale optimization algorithm (WOA), respectively.

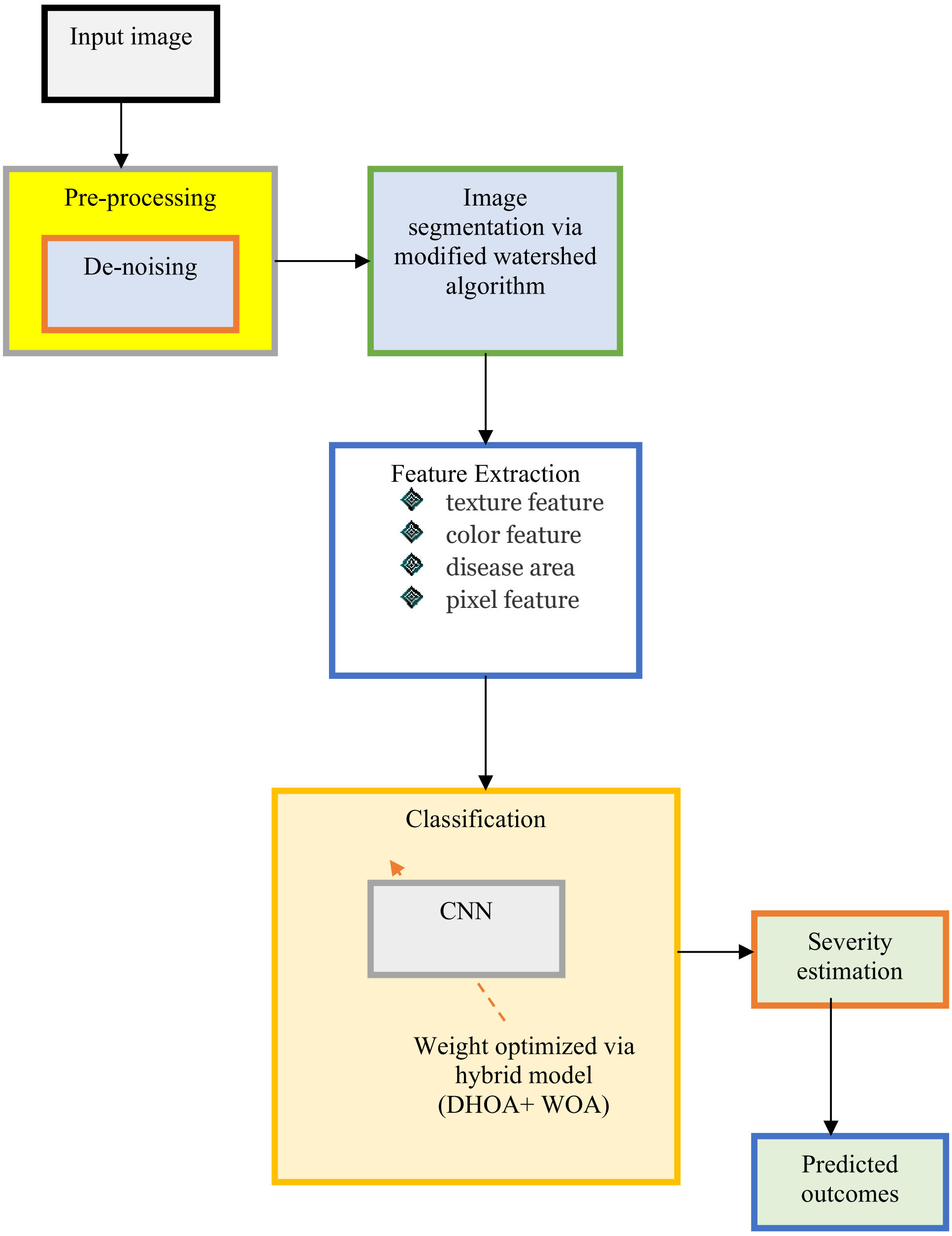

Figure 1: Architecture of the proposed work

III.CONCLUSION

This research work focuses the survey on different diseases classification techniques used for plant leaf disease detection and an algorithm for image segmentation technique that can be used for automatic detection as well as classification of plant leaf diseases. In proposed architecture image will be de-noised and segmented. Features will be fed as input to the detection phase that use Convolutional Neural network (CNN) for disease identification. Further, to enhance the classification accuracy of the disease, the weight of CNN will be fine-tuned via a new hybrid model. Moreover, the final prediction results will be based on the estimation of severity.

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