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Advancements in Deep Learning for Early Detection of Plant Diseases: Techniques, Challenges, and Opportunities in Precision Agriculture

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Abstract: Deep learning (DL) has emerged as a transformative technology in the field of agriculture, revolutionizing various applications such as disease recognition, plant classification, and fruit counting. Compared to traditional image processing techniques, deep learning has demonstrated a remarkable ability to achieve significantly higher accuracy, surpassing the performance of conventional methods.One of the primary advantages of leveraging deep learning in agriculture is its unparalleled capacity to provide more precise predictions, enabling farmers and researchers to make better-informed decisions that lead to improved outcomes. Deep learning models have consistently exhibited impressive performance across a wide range of tasks, including visual recognition, language processing, and speech detection, making them highly suitable for diverse agricultural applications. Furthermore, the success of deep learning in medical imaging has been successfully extended to the agricultural domain. By applying deep learning's powerful capabilities, stakeholders in the agricultural sector can now accurately classify plant species, detect diseases, and identify pests with unprecedented precision. This advancement has the potential to drive significant improvements in productivity, reduce crop losses, and optimize resource allocation, ultimately transforming the way we approach agricultural practices.

Keywords: *DNN, CNN, DL-Deep Learning, Transfer Learning, Ensemble learning*

1. Introduction:

Detection of plant diseases in its early stage is crucial for maintaining crop quality and yield, as well as reducing unnecessary drug use and costs[1]. The use of machine learning and deep learning methods, such as image processing and transfer learning, has significantly improved the accuracy and efficiency of disease detection[2] [3]Traditional methods, such as visual observation and microscopy, are still widely used, but innovative technologies like immunodiagnostics and molecular-genetic identification are increasingly being adopted for their rapid and reliable results These advancements in disease detection are essential for ensuring timely intervention and preventing crop losses.

Deep learning has shown great potential in agriculture, particularly in plant disease detection. Ale [4] and Santos [5] both highlight the accuracy and efficiency of deep learning models in this area. Ale [4] specifically introduces a Densely

Connected Convolutional Networks (DenseNet) based transfer learning method for plant disease detection, while Santos [5]provides a comprehensive survey of deep learning techniques in agriculture, including disease detection. [6] addresses the limitations of existing plant disease detection models and introduces a large dataset for training and evaluation. Turkoglu [7] further explores the use of deep learning-based features for plant disease and pest detection, finding that deep feature extraction and “support vector machine” (SVM) or “extreme learning machine “(ELM) classification produce better results than transfer learning. These studies done so far underscore the strength of deep learning in agriculture, particularly in the detection of plant diseases.

Deep learning (DL) has been widely applied in agriculture for various tasks such as disease detection, plant classification, and fruit counting. It has been used to achieve high accuracy in these applications, surpassing traditional image processing techniques [5] The advantages of using deep learning in agriculture include its ability to offer more correct estimates than traditional methods, enabling better decision-making.[6] Additionally, Deep learning models have demonstrated remarkable capabilities in various domains, including visual recognition, language processing, and speech detection. These impressive performances make deep learning a highly suitable approach for agricultural applications. [8]Furthermore, deep learning technology has been effectively working as a strong tool in image classification as well as disease detection created on medical images, which can be extended to agriculture domain too [8].

In summary, the research on plant disease recognition using traditional image processing techniques has achieved some success, with high accuracy in disease identification. However, there are still several limitations: The research process is bulky, often subjective, slow, and labor-intensive as well as deeply relies on accurate segmentation of disease spots.

It heavily depends on manual feature extraction

Evaluating the disease recognition performance of models or algorithms in complex real-world environments poses significant challenges. Therefore, it is crucial to develop intelligent, rapid, and accurate plant leaf disease recognition methods. In recent years, deep learning (DL) technology has made significant progress in this field. Deep learning offers several advantages:

It is transparent to the user, making it accessible to researchers in plant protection and statistics, even with limited technical expertise.

Deep learning can automatically extract image features and classify plant diseases, eliminating the need for manual feature extraction and classifier design, which are required in traditional image recognition techniques.

Deep learning can effectively express the original image characteristics and has an end-to-end architecture.

These characteristics have made deep learning a popular and widely-studied approach for plant disease recognition. This is due to three key factors:

The readily available larger datasets for training deep learning models.

The adaptability of multi-core graphics processing units (GPUs) for efficient deep learning computations.

The development of training deep neural networks has been greatly facilitated by the availability of supporting software libraries, such as the Computing Unified Device Architecture (CUDA) from NVIDIA. CUDA provides a parallel computing platform and programming model that enables efficient utilization of NVIDIA GPUs for accelerating deep learning workloads.

In summary, the research on plant disease recognition has evolved from traditional image processing techniques to the more advanced deep learning approaches, which offer significant advantages in terms of automation, accuracy, and adaptability to complex environments.

2. Deep Learning For Identifying Plant Diseases:

The studies on deep learning for plant disease detection have primarily employed convolutional neural networks (CNNs) and related architectures. Here are the key studies and their categorization based on the types of deep learning models used:

1. **CNNs and Related Architectures:**

"A Systematic Study: Implication of Deep Learning in Plant Disease Detection" by Bonkra et al. employed CNNs for diagnosing and forecasting plant diseases using hyper spectral images.

"Plant Disease Detection and Classification by Deep Learning—A Review"[9]discussed the use of CNNs for plant disease detection and classification.

"Deep learning models for plant disease detection and diagnosis" [10] developed CNN models for plant disease detection and achieved a 99.53% success rate in identifying plant diseases.

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2. **Transfer Learning and Ensemble Models:**

"Deep Learning based Plant Disease Detection for Smart Agriculture" [4] proposed a transfer learning method using DenseNet and a lightweight DNN approach for plant disease detection.

3. **Visualization and Feature Extraction:**

"New perspectives on plant disease characterization based on deep learning" studied CNNs and visualization techniques for plant disease detection.[11]

4. **Ensemble Classification and Feature Extraction:**

"Crop leaf disease classification identification based on ensemble" [13] explored machine learning techniques, including deep learning, for disease recognition or identification on rice leaves.

The strengths of deep learning in image-based disease identification include its ability to automatically learn and extract features from images, enabling accurate and efficient detection of plant diseases. Deep learning models, particularly CNNs, have demonstrated high accuracy in identifying plant diseases from images, making them valuable tools for early disease detection and classification [9]. Additionally, deep learning models can be fine-tuned and adapted to different plant species and diseases, providing flexibility and scalability in disease identification [10]. The use of visualization techniques in deep learning models also enhances the interpretability and transparency of disease detection, contributing to improved understanding and diagnosis of plant diseases.

These studies collectively highlight the robustness and effectiveness of deep learning, particularly CNNs, in image-based plant disease identification, offering promising solutions for addressing agricultural challenges related to disease detection and crop management.

Table 1: **comparison on the plant disease detection techniques used in deep learning**

paper	plant disease detection techniques used in deep learning	merits	demerits
[11] 'New perspectives on plant disease characterization based on deep learning'	The study looks at deep learning-based automatic image recognition algorithms that are used today to identify plant illnesses in earlier stage. The practice of improving previously trained models on plant identification tasks is known as transfer learning, which is the process of doing refinement of pre-trained models made for plant identification tasks. The study also introduces a more instinctive technique that ponders diseases independently of crops, which is shown to be more effective than the classic crop-disease pair approach.	The methodology used in the paper has several merits. Firstly, the study investigates the effect of transfer learning strategies, comparing the effectiveness of fine-tuning a model which is pre-trained for the identification of plant with one pre-trained on general object recognition. Secondly, the paper proposes a new approach to characterizing plant diseases independently of the type of crop, It demonstrates increased robustness and generalizability in diagnosing illnesses in new data and unseen crops. Lastly, the study evaluates the robustness	The limitations of the experiment include the lack of diversity in the plant disease dataset, which may lead to overfitting of deeper network architectures. Additionally, the study suggests that the size of the field test sets, IPM and Bing, may be too small to generalize the results. Furthermore, the study highlights the need for a broader and more diversified plant disease database to improve the accuracy of final target tasks.

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		of deep learning models for predicting plant diseases on exterior images, providing insights into the deep model's cross-domain generalization to enhance illness detection.	
[10] 'Deep learning models for plant disease detection and diagnosis'	The technique used for detecting plant diseases in this research is the development of convolutional neural network (CNN) models. These models were trained using a large dataset of images of healthy and diseased plants, and the best performing model The deep learning model achieved an exceptionally high success rate of 99.53% in accurately identifying the corresponding combination of plant species and disease.	There are various advantages to the paper's methodology. It was able to detect the relevant [plant, disease] combination with a success percentage of 99.53%. The deep learning models created for the diagnosis and detection of plant diseases demonstrated great promise. The models perform better when trained on photos taken in the field and asked to recognize images taken in a lab. This highlights how crucial it is to have photos taken under real-world conditions of cultivation in order to create effective and practical automated plant disease detection and diagnostic systems.	The limitations of the experiment include the use of images solely from laboratory setups, which may not reflect real conditions in cultivation. Additionally, the training/testing ratio was not ideal, and the testing dataset was part of the same database as the training set, which may limit the generalizability of the results. Finally, the model's performance was reduced when tested on data from different sources, indicating a need for a wider variety of training data.
[12] 'Non-destructive techniques of detecting plant diseases'	The techniques and methodologies used for detecting plant diseases include photograph-based approaches, crop image processing approaches, spectroscopy-based approaches, and remote sensing applications. Image-based and image processing approaches for plant disease recognition typically	The paper discusses several non-destructive techniques for detecting plant diseases, including image-based approaches, image processing approaches, spectroscopy-based approaches, and remote sensing application. The merits of these methodologies include the ability to provide real-time monitoring,	The limitations of the experiment include the difficulty of discriminating healthy plants from diseased ones using airborne multispectral remote sensing imagery. Additionally, the deficiency of frequency bandwidth is a drawback of the electric impedance spectroscopy method.

	involve a series of steps, including image acquisition, pre-processing, segmentation, feature extraction, and classification, while spectroscopy-based approaches rely on the interface between the spectrum of electromagnetic signls and the diseased plant. Remote sensing applications include hyperspectral and multispectral remote sensing.	early detection of diseases, and the potential for analysing disease spread. Additionally, these techniques offer the advantage of being non-destructive, meaning they do not cause damage to the plants during the detection process.	
[4] ‘Deep Learning Based Plant Disease Detection for Smart Agriculture’	The research paper discusses the use of deep learning models, specifically Densely Connected Convolutional Networks (DenseNet) and Deep Neural Networks (DNN), for detecting plant diseases. The researchers introduce a novel approach that leverages a DenseNet architecture and transfer learning techniques to enable accurate detection of plant diseases. This method is designed to be deployed on edge servers with enhanced computational capabilities, allowing for efficient and distributed processing of plant disease detection tasks. Additionally, they put forth a lightweight DNN method which can be executed on Internet of Things (IoT) devices having constrain over the use of resources. The	The methodology used in the paper has several merits. First, it proposes a lightweight deep learning model that can run on IoT devices with limited computing capacities, such as smartphones. Second, the proposed model is relatively smaller than other classical deep learning models, making it deployable on mobile edges or powerful IoT devices. Third, the paper discusses the benefits of data augmentation, which can prevent overfitting, improve prediction accuracy, and help the model deal with unseen data more robustly. Finally, the experimental results show that the transfer learning model can achieve high accuracy and can run on mobile edge servers.	The limitations of the experiment include the fact that the suggested new lightweight deep learning model might miss few features and intern make a compromise in the performance when input images are resized to low resolutions. Additionally, high-resolution images convey more information but make the total computational costs increase exponentially. The training learning curves more likely becomes smoother as compared to validation curves, indicating that the models tend to fit the training dataset more, which could lead to overfitting. Finally, the proposed lightweight deep learning model may not achieve extremely high accuracy, making it unsuitable for applications requiring

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	method trained the model by taking different sizes of image to conclude upon which is the appropriate size of the input images. The proposed models are evaluated based on real-world datasets and are shown to accurately detect plant diseases using relatively low computational resources.		high accuracy on high-performance computers.

3. Datasets For Training And Evaluation :

The datasets commonly used in training and evaluating “deep learning models for plant disease detection “include the “Plant Village dataset, the Plant Pathology Challenge dataset”, and datasets collected from real-world conditions. The Plant Village dataset is a large open dataset containing images of the category of healthy and diseased crops both with a range of diseases, categorized into fungi, bacteria, Mold, virus, and mites[8]. It contains 54,323 images divided into 38 classes of diseased and healthy plants based on 14 different crop species [11]. The dataset is well-labelled and has been adopted in many plants disease detection research [4]. Though, it is significant to make a note that the dataset was taken in a controlled environment, which may limit its generalizability to real-world conditions [6].

The Plant Pathology Challenge dataset is another commonly used dataset for plant disease detection. This dataset was used for the CVPR 2020-FGVC7 challenge and contains real disease and pest images from Turkey. The dataset is valuable for evaluating deep learning models for plant disease detection in real-world conditions.

In addition to these large datasets, smaller datasets are also used for specific research purposes. For example, some datasets contain few images or even dozens of images showing diseases, which can be challenging for training deep learning models [9]. These datasets may require transfer learning to adapt the knowledge learned from larger datasets to the specific conditions of the smaller dataset [9].

The characteristics of these datasets vary in terms of size, diversity, and annotation quality. The Plant Village dataset is large and diverse, covering a wide range of diseases and crop species. However, it is important to consider that the dataset was collected in a controlled environment, which may limit its diversity in terms of real-world conditions. On the other hand, datasets collected from real-world conditions may offer greater diversity but may be smaller in size and require careful annotation to ensure high quality for training and evaluation[6].

In summary, the datasets commonly used in training and evaluating deep learning models for plant disease detection vary in size, diversity, and annotation quality. Large datasets like Plant Village provide a wide range of images for training, while datasets collected from real-world conditions offer greater diversity but may require careful curation and annotation to ensure high quality for training and evaluation.

4. Performance Metrics and Benchmarking:

The performance metrics used to evaluate the effectiveness of deep learning models in plant disease detection include accuracy, sensitivity, specificity, and F1-score [7]. In the context of plant disease recognition, accuracy measures the proportion of instances that were correctly classified as having a particular disease or being disease-free. Sensitivity, on the other hand, refers to the ability of the experiment or model to correctly identify the actual positive cases, meaning the proportion of diseased plants that were accurately detected. Specificity gives a measure of the proportion of total negative cases that were identified correctly, and F1-score is the harmonic mean of precision and recall, providing a balance between the two [7].

In the field of deep learning for plant disease detection, standard benchmarks for fair comparison include the use of real disease and pest images from diverse sources, such as images from different geographic areas and under various conditions [6]. Additionally, the use of large datasets, such as a dataset consisting of 1965 real plant disease and pest images within eight clusters, has been employed to establish benchmarks for fair comparison [7] These benchmarks ensure that the deep learning models are tested on a wide range of real-world scenarios, leading to more robust and reliable performance evaluations.

5. Comparison with Traditional Methods:

Deep learning approaches have shown increased accuracy and speed compared to traditional methods in the identifying and classifying plant diseases. Deep learning models have been found to provide results with improved accuracy, exceedingly more conventional alternative image processing methods in terms of accuracy [5]. They have also been reported to achieve high precision and to be faster in testing time compared to classic methods like Support Vector Machine (SVM) or Scale-invariant feature transform (SIFT) [5]. Additionally, deep learning models have been shown to achieve high accuracy in the majority of reviewed works, scoring higher precision than other traditional techniques [5]. The advantages of deep learning models include their ability to learn features directly and represent them successively in hierarchical architectures, as well as their capability to perform feature extraction without applying segmented methods, making them suitable for real-life applications [7]. Furthermore, deep learning models have been found to provide better results compared to traditional methods, with deep feature extraction and SVM/ELM classification obtaining higher classification accuracy than networks based on transfer learning [7]. In summary, deep learning approaches offer increased accuracy and speed compared to traditional methods, making them suitable for real-life applications and providing high precision in the detection and classification of plant diseases.

6. Challenges in Deep Learning-Based Plant Disease Detection:

Applying deep learning algorithms for plant disease detection presents several challenges and limitations. One of the prime challenges is the availability of superior-quality databases. The accuracy of any deep learning model can go better and better upon the availability of large-scale datasets[8]. However, collecting datasets that accurately represent diverse environmental conditions and disease stages is difficult. The unavailability of public data base and the challenging nature of the datasets generate important opportunities for compensating upcoming research opportunities [8]. Additionally, the datasets used for training deep learning models should ideally contain images captured in different conditions to ensure robustness and generalization to diverse environmental conditions [6].

Another challenge is the interpretability of deep learning models. While deep learning models have shown impressive performance in plant disease detection, the interpretability of these models remains a concern. Visualizing the characteristics learned by deep learning models and understanding how they contribute to disease detection is crucial for model interpretability [11]. The characteristics learned by deep learning models may not necessarily focus on the part affected by the disease, which can impact the interpretability of the models [11].

Generalizing deep learning models to diverse environmental conditions is another limitation. Deep learning models trained on datasets from controlled environments may not perform well when tested in real conditions. The lack of images gathered and labelled from real-life situations is a limitation, as training is often conducted with images taken in controlled environments [6]. Furthermore, the ability of deep learning models to detect multiple diseases in one image or multiple occurrences of the same disease in one image is also a limitation that needs to be addressed [6]. In summary, the challenges and limitations in applying deep learning to plant disease detection include the availability of high-quality datasets representing diverse environmental conditions, the interpretability of deep learning models, and the generalization of models to real-life situations and diverse disease scenarios.

7. Recent Advances and Innovations:

Recent advancements in the field of deep learning for plant disease detection and classification include the use of novel architectures, transfer learning techniques, and multi-modal approaches. Novel architectures such as DenseNet and Densely Connected Convolutional Networks (DenseNet) have been proposed for detecting plant diseases with high accuracy, even on devices with limited computational resources [4]. Transfer learning methods have been used to fine-tune pre-trained models for plant disease classification, enabling the use of large-scale pre-trained models to improve accuracy and performance [11]. Additionally, multi-modal approaches, such as combining vegetation indices in colour space with deep learning models, have been explored for detecting crop diseases [9]. These advancements have contributed to improved accuracy, interpretability, and scalability in the field of plant disease detection using deep learning.

8. Integration with Precision Agriculture:

Deep learning in plant disease detection aligns with the principles of precision agriculture by enabling early disease detection and targeted intervention, which are essential for resource optimization and sustainable farming practices. By identifying diseases at an early stage, precision agriculture can minimize the use of pesticides and fertilizers, reduce crop losses, and improve overall crop quality. This approach can lead to more efficient resource allocation, reduced environmental impact, and increased sustainability in agricultural practices. The use of deep learning in plant disease detection has been shown to provide highly accurate results, especially in the early detection and classification of plant diseases. The early detection of plant diseases is a fundamental aspect of precision agriculture, as it allows for targeted treatment and management of affected crops, reducing the need for broad-spectrum treatments and minimizing the environmental impact of agricultural practices [6]. By leveraging deep learning models, precision agriculture can optimize the use of resources such as water, fertilizers, and pesticides, leading to more sustainable farming practices [6] Furthermore, deep learning models can be integrated with precision agriculture technologies, such as IoT devices and edge servers, to enable real-time disease detection and monitoring in the field [4]. This integration allows for timely and targeted interventions, reducing the overall environmental impact of agricultural practices and contributing to sustainable farming [4]. In summary, the application of deep learning in plant disease detection aligns with the principles of precision agriculture by enabling early disease detection, targeted intervention, and optimized resource allocation. These implications contribute to more sustainable farming practices, reduced environmental impact, and improved overall crop quality.

9. Conclusion:

The literature review on plant disease detection using deep learning techniques highlights several key findings. Deep learning has been widely applied in the field of plant disease detection, offering advantages such as automatic learning, feature extraction, and improved research efficiency [9]. Recent studies have focused on using deep learning models, such as convolutional neural networks (CNNs), for the early detection and classification of plant diseases [9]. The use of deep learning has led to significant progress in recognizing and classifying plant diseases, with some models achieving high accuracy rates, such as 93.67%. Additionally, the application of deep learning in agriculture has shown promise for smart agriculture, enabling the detection of plant diseases with low computational resources. Advancements in plant disease detection through deep learning include the development of novel datasets containing many labelled images of leaves captured in real surroundings, as well as the use of state-of-the-art style generative adversarial networks for image augmentation [6]. Furthermore, the use of deep learning models, such as Dense Net and DNN, has shown promise for detecting plant diseases with high accuracy, even in real-world scenarios. However, there are gaps in the current research that may warrant further investigation. For example, there is a need for better robustness in deep learning models to adapt to diverse disease datasets, as the effects of the models are not consistent across different datasets. Additionally, there is a lack of comprehensive studies addressing the challenges of using real-world datasets for plant disease detection, including issues [12]such as data scarcity, accurate disease classification, and disease stage identification [6]. Moreover, there is a need to explore the potential of fine-tuning pre-trained models for plant disease detection and to consider diseases independently of crops to improve the effectiveness of disease detection, especially for diseases involving crops not illustrated in the training database [11]. In summary, the application of deep learning in plant disease detection has shown significant progress, but there are opportunities for further research to address the challenges and limitations in real-world applications, dataset robustness, and fine-tuning of models for improved disease detection.

References:

[1] U. B. Korkut, O. B. Gokturk, and O. Yildiz, “Detection of plant diseases by machine learning,” in 2018 26th Signal Processing and Communications Applications Conference (SIU), IEEE, May 2018, pp. 1–4. doi: 10.1109/SIU.2018.8404692.

[2] N. Kaur, V. Devendran, and S. Verma, “Detection of Plant Leaf Diseases by Applying Image Processing Schemes,” J Comput Theor Nanosci, vol. 16, no. 9, pp. 3728–3734, Sep. 2019, doi: 10.1166/jctn.2019.8241.

[3] F. Akhtar, N. Partheeban, A. Daniel, S. Sriramulu, S. Mehra, and N. Gupta, “Plant Disease Detection based on Deep Learning Approach,” in 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), IEEE, Mar. 2021, pp. 74–77. doi: 10.1109/ICACITE51222.2021.9404647.

[4] L. Ale, A. Sheta, L. Li, Y. Wang, and N. Zhang, “Deep Learning Based Plant Disease Detection for Smart Agriculture,” in 2019 IEEE Globecom Workshops (GC Wkshps), IEEE, Dec. 2019, pp. 1–6. doi: 10.1109/GCWkshps45667.2019.9024439.

[5] L. Santos, F. N. Santos, P. M. Oliveira, and P. Shinde, “Deep Learning Applications in Agriculture: A Short Review,” 2020, pp. 139–151. doi: 10.1007/978-3-030-35990-4_12.

[6] M. Arsenovic, M. Karanovic, S. Sladojevic, A. Anderla, and D. Stefanovic, “Solving current limitations of deep learning-based approaches for plant disease detection,” Symmetry (Basel), vol. 11, no. 7,

Jul. 2019, doi: 10.3390/sym11070939.

[7] M. TÜRKOĞLU and D. HANBAY, “Plant disease and pest detection using deep learning-based features,” TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES, vol. 27, no. 3, pp. 1636–1651, May 2019, doi: 10.3906/elk-1809-181.

[8] R. I. Hasan, S. M. Yusuf, and L. Alzubaidi, “Review of the state of the art of deep learning for plant diseases: A broad analysis and discussion,” Plants, vol. 9, no. 10. MDPI AG, pp. 1–25, Oct. 01, 2020. doi: 10.3390/plants9101302.

[9] L. Li, S. Zhang, and B. Wang, “Plant Disease Detection and Classification by Deep Learning—A Review,” IEEE Access, vol. 9, pp. 56683–56698, 2021, doi: 10.1109/ACCESS.2021.3069646.

[10] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Comput Electron Agric, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009.

[11] S. H. Lee, H. Goëau, P. Bonnet, and A. Joly, “New perspectives on plant disease characterization based on deep learning,” Comput Electron Agric, vol. 170, p. 105220, Mar. 2020, doi: 10.1016/j.compag.2020.105220.

[12] M. M. Ali, N. A. Bachik, N. ‘Atirah Muhadi, T. N. Tuan Yusof, and C. Gomes, “Non-destructive techniques of detecting plant diseases: A review,” Physiol Mol Plant Pathol, vol. 108, p. 101426, Dec. 2019, doi: 10.1016/j.pmpp.2019.101426.

[13] Kaur, N. V. D. sahil V. (2021). Crop leaf disease identification based on ensemble classification. Algorithms, Computing and Mathematics Conference, 110–118.

[14] J. G. Ha, H. Moon, J. T. Kwak, S. I. Hassan, M. Dang, O. N. Lee, and H. Y. Park, Deepconvolutional neural network for classifying Fusarium wilt of radish from unmanned aerial vehicles, J. Appl. Remote Sens., vol. 11, no. 4, p. 1, Dec. 2017.

[15] J. G. A. Barbedo, Plant disease identi cation from individual lesions and spots using deep learning, Biosyst. Eng., vol. 180, pp. 96107, Apr. 2019.

[16] S. Ghosal, D. Blystone, A. K. Singh, B. Ganapathy subramanian, A. Singh,and S.Sarkar, An explainable deep machine vision framework for plant stress phenotyping, Proc. Nat. Acad. Sci. USA, vol. 115, no. 18, pp. 46134618, Apr. 2018.

[17] Y.Lu,S.Yi,N.Zeng,Y.Liu,andY.Zhang, Identi cationofricediseases using deep convolutional neural networks, Neurocomputing, vol. 267, pp. 378384, Dec. 2017.

[18] A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, Deep convolutional neural networks for mobile capture device-based crop disease classi cation in the wild, Comput. Electron. Agricult., vol. 161, pp. 280290, Jun. 2019.

[19] A. Johannes, A. Picon, A. Alvarez-Gila, J. Echazarra, S. Rodriguez-Vaamonde, A. D. Navajas, and A. Ortiz-Barredo, Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case, Comput. Electron. Agricult., vol. 138, pp. 200209, Jun. 2017.

[20] M. A. Khan, T. Akram, M. Sharif, M. Awais, K. Javed, H. Ali, and T. Saba, CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coef cient and deep CNN features, Comput. Electron. Agricult., vol. 155, pp. 220236, Dec. 2018.

[21] M. Kerkech, A. Ha ane, and R. Canals, Deep leaning approach with colorimetric spaces and vegetation indices for vine diseases detection in UAV images, Comput. Electron. Agricult., vol. 155, pp. 237243, Dec. 2018.

[22] K. Nagasubramanian, A. K. Singh, A. Singh, S. Sarkar, and B. Ganapathysubramanian, Usefulness of interpretability methods to explain deep learning based plant stress phenotyping, Comput. Sci., vol. 4, pp. 1832, Jul. 2020

[23] Z.-W. Hu, H. Yang, J.-M. Huang, and Q.-Q. Xie, Fine-grained tomato disease recognition based on attention residual mechanism, J. South China Agricult. Univ., vol. 40, no. 6, pp. 124132, Jul. 2019.

[24] S. H. Lee, H. Goëau, P. Bonnet, and A. Joly, New perspectives on plant disease characterization based on deep learning, Comput.Electron. Agricult., vol. 170, Mar. 2020, Art. no. 105220

[25]] R. Mittler and E. Blumwald, “Genetic engineering for mod ern agriculture: Challenges and perspectives,” Annual Review of Plant Biology, vol. 61, no. 1, pp. 443–462, 2010, pMID: 20192746.

[26] F. Caffaro, M. Roccato, M. M. Cremasco, and E. Cavallo, “Falls from agricultural machinery: Risk factors related to work expe rience, worked hours, and operators behavior,” Human Factors, vol. 60, no. 1, pp. 20–30, 2018.

[27] R. N Strange and P. Scott, “Plant disease: A threat to global food security,” Annual review of phytopathology, vol. 43, pp. 83 116, 02 2005

[28] Y. Sun, Z. Jiang, L. Zhang, W. Dong, and Y. Rao, SLIC_SVM based leaf diseases saliency map extraction of tea plant, Comput. Electron. Agricult., vol. 157, pp. 102109, Feb. 2019.