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A Detailed Review on Plant Leaf Disease Detection and Classification Methodologies using Deep Learning Techniques

Penugonda Seetha Rama Krishna[1], Dr. S Nagarajan[2]
[1]Research Scholar, Regd. No: 2136070008, Dept. of Computer Science Engineering, Annamalai University, Chidambaram, Tamilnadu
[2]Associate Professor & Research Supervisor, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Annamalai University
psrkrishna04@gmail.com[1], naga72.aucse@gmail.com[2]

ABSTRACT:

The rapid emergence and evolution of deep learning methodologies in the field of plant disease classification and detection has resulted in significant progress. Their application has revolutionized the way agriculture is done. This paper provides an overview of the advancements in utilizing deep learning models to address the crucial task of identifying and categorizing plant diseases. By harnessing the power of deep convolutional neural networks (CNNs) and transfer learning, researchers have achieved remarkable accuracy in disease classification, often surpassing traditional methods. This study also delves into the challenges that persist in this field, such as the scarcity of labeled data and potential biases in models. To address these concerns, the integration of visualization techniques is explored, allowing for better model interpretation and transparency. The collaborative efforts of agricultural experts and machine learning researchers are deemed crucial for overcoming these challenges and driving the future direction of research. Looking ahead, the interdisciplinary approach is anticipated to play a pivotal role in refining deep learning models for plant disease detection. A seamless collaboration between domain-specific professionals, machine learning experts, and agricultural practitioners is essential to foster innovation, enhance the reliability of models, and create a sustainable agricultural ecosystem. With the integration of cutting-edge architectures, emerging technologies like edge computing, and broader datasets, the field is poised to bring about transformative changes in agricultural practices, bolstering crop health and productivity.

Keywords: Convolutional Neural Networks, Deep Learning models, GoogleNet, AlexNet, Visualization Technique.

1. INTRODUCTION

Technological advancements have significantly changed the way agriculture is practiced over the past few years. These include the identification and classification of plant diseases. These threats have the potential to significantly affect the global food supply. The accuracy and timeliness of the diagnosis of plant diseases are vital for implementing effective strategies to safeguard the global food supply and ensure the sustainability of crop production. In the past, this process was laborious, time-consuming, and prone to subjectivity. However, with the advent of deep learning techniques, particularly convolutional neural networks (CNNs) and their variants, a paradigm shift has occurred in disease detection and classification. These techniques have demonstrated remarkable capabilities in automating the detection process by analyzing visual cues present in plant leaf images [1].

In figure 1 we can see the flow diagram of how deep learning can be used to classify and identify diseases in plant leaves. The process begins with Data Collection, where a dataset of plant leaf images containing both healthy and diseased samples is gathered. These images undergo Data Preprocessing, involving resizing, pixel value normalization, and augmentation techniques. The next step involves Model Selection, where an appropriate deep learning architecture, typically CNN, is chosen. This Model Architecture outlines the specifics of the chosen CNN, including layer configurations and filter sizes. Next, we separate the training data into its two components: validation and training. One uses the other to evaluate the model's performance, while the other is used for training it. To gain insights into the model's decision-making process, various Visualization Techniques are applied. These include techniques like saliency maps, activation maps, and heatmaps, which provide a deeper understanding of the regions the model focuses on for disease detection [2].

The paper reviews the different methodologies utilized in plant leaf disease classification and detection. Deep learning is used in this study. Researchers have developed efficient and robust models that can differentiate between diseased and

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healthy plant leaves by using deep neural networks. The use of deep learning techniques has not only expedited the diagnosis process but has also opened avenues for scalability, enabling the rapid assessment of large agricultural landscapes. In this context, this review aims to provide a detailed exploration of the various deep learning approaches applied to plant leaf disease detection and classification. It delves into the intricacies of preprocessing techniques, data augmentation, and normalization methods that contribute to enhancing model performance. Additionally, the review critically examines the challenges posed by imbalanced datasets, exploring potential solutions and their impact on overall model efficacy.

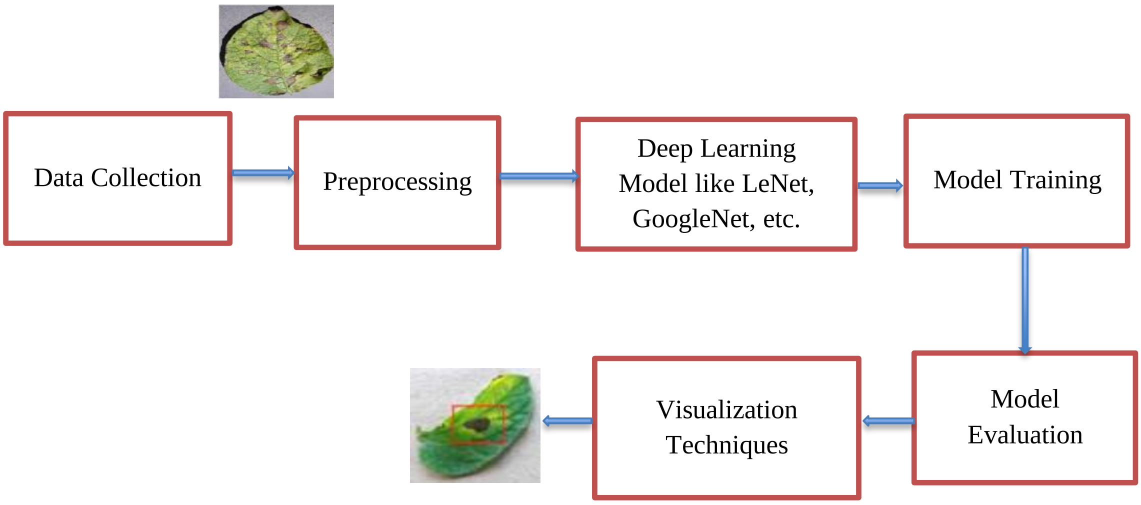

Figure 1. General Flow diagram of plant leaf disease detection and classification

Furthermore, this review sheds light on the significance of benchmark datasets, which serve as a foundation for evaluating the performance of different deep learning models. It also investigates the wide array of evaluation metrics, loss functions, and optimization algorithms employed to quantify the accuracy and efficiency of disease classification models. As the agricultural community continues to grapple with the consequences of plant diseases, the integration of transfer learning and domain adaptation emerges as a pivotal strategy for maximizing the potential of deep learning models. This review explores how pre-trained models can be fine-tuned to cater to specific plant species and disease types, thereby enabling the development of adaptable and generalized disease detection systems. This review aims to contribute to the development of a plant disease detection system using deep learning. It draws on various perspectives and methodologies to address the challenges and opportunities associated with this field. As researchers and practitioners strive to address the ever-evolving demands of modern agriculture, this comprehensive examination serves as a valuable resource, guiding the development of innovative and impactful solutions for ensuring global food security and sustainable agricultural practices.

2. DATASETS

Various publicly available datasets are utilized in the study and development of machine learning models for the classification and detection of plant diseases.

PlantVillage Dataset [3]: A popular collection, PlantVillage includes pictures of both healthy and diseased plants. This database is beneficial for training and assessing disease detection models since it includes a broad variety of plant species and diseases.

Tomato Leaf Disease Dataset [4]: The dataset pertains to tomato plant diseases, and it features images of leaves infected with various types of infections, including bacterial spots, early blight, and late blight.

Cassava Leaf Disease Dataset [5]: Images of diseased cassava leaves, including brown streak and mosaic illnesses, are included in this set. Cassava is a staple crop in many places.

Rice Disease Dataset [6]: Diseases affecting rice, such as rice blast and bacterial leaf blight, are the subject of many databases, despite rice's enormous importance as a crop.

Citrus Pest and Disease Image Dataset [7]: This dataset includes images of various citrus crops affected by pests and diseases, providing a valuable resource for citrus disease research.

DeepWeeds Dataset [8]: While not focused solely on diseases, the DeepWeeds dataset includes images of various weed species that can compete with crops and contribute to overall plant health issues.

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Apple Disease Dataset [9]: With a focus on apple trees, this dataset includes images of apple leaves affected by diseases such as apple scab and apple rust.

Flavia Dataset [10]: The Flavia dataset includes images of leaf images from four different plant species with various diseases. It's often used for research on leaf classification and disease detection.

LeafSnap Dataset [11]: While primarily focused on leaf identification, LeafSnap also includes images of leaves with diseases and pests, making it a valuable resource for general plant health research.

EuroBlight Potato Disease Image Database [12]: This dataset focuses on diseases affecting potato plants, including images of leaves affected by diseases like late blight and early blight.

3. DEEP LEARNING MODELS

LeNet [13], being the pioneering CNN model, features a simpler structure with fewer parameters compared to its more advanced counterparts. This simplicity, however, comes with limitations in terms of computational capacity, as it cannot accommodate complex tasks as effectively as later CNN models. It is introduced by Yann LeCun et al. in 1998. AlexNet [14], notable for its 60 million parameters, holds the distinction of being the inaugural modern CNN. It achieved exceptional image recognition capabilities during its era and introduced the utilization of ReLU activation functions to enhance performance. To counter overfitting, AlexNet employed the dropout technique.

OverFeat [15]: It is introduced by Pierre Sermanet et al. in 2013. Equipped with 145 million parameters, OverFeat marked the first instance of a model serving triple roles - object detection, localization, and classification - using a single CNN. This parameter count surpasses that of AlexNet.

ZFNet [15]: It is developed by Matthew D. Zeiler and Rob Fergus in 2013. With 42.6 million parameters, ZFNet introduced a compact configuration by employing 7x7 kernels, leading to enhanced accuracy while maintaining reduced weight as compared to AlexNet.

VGG [15]: It is proposed by Karen Simonyan and Andrew Zisserman in 2014. With parameter counts ranging from 133 to 144 million, VGG's innovation lies in its incorporation of 3x3 receptive fields. This inclusion of numerous non-linearity functions contributes to a more discriminative decision function. However, the model's computational complexity escalates due to the high number of parameters.

GoogLeNet [15]: Boasting 7 million parameters, GoogLeNet stood out with a lower parameter count compared to the AlexNet model. Its accuracy exceeded contemporaneous models. Introduced by Christian Szegedy et al. in 2014.

ResNet [16]: Weighing in at 25.5 million parameters, ResNet tackled the vanishing gradient issue. This architectural feat resulted in superior accuracy compared to VGG and GoogLeNet models. Developed by Kaiming He et al. in 2015.

DenseNet [16]: With 7.1 million parameters, DenseNet employs densely interconnected layers, resulting in reduced parameter count while attaining improved accuracy. Proposed by Gao Huang et al. in 2016.

SqueezeNet [16]: Boasting a mere 1.25 million parameters, SqueezeNet matches AlexNet's accuracy while utilizing 50 times fewer parameters. This approach incorporates 1x1 filters, diminishes input channels, and generates substantial activation maps for convolution layers. It was introduced by Forrest N. Iandola et al. in 2016

Xception [16]: Tallying at 22.8 million parameters, Xception adopts a depth-wise separable convolution methodology, surpassing VGG, ResNet, and Inception-v3 models in terms of performance. It was developed by François Chollet in 2017.

MobileNet [16]: It is introduced by Andrew G. Howard et al. in 2017. Comprising 4.2 million parameters, MobileNet adopts depth-wise separable convolutions, significantly trimming parameter load while achieving accuracy levels akin to VGG and GoogLeNet. It was introduced by Andrew G. Howard et al. in 2017. Modified/Reduced MobileNet: Boasting 0.5/0.54 million parameters, this version of MobileNet further reduces parameter count while maintaining comparable accuracy. VGG-Inception: With 132 million parameters, VGG-Inception amalgamates VGG and inception modules. Parameter count reduction is achieved by replacing 5x5 convolution layers with dual 3x3 layers, resulting in elevated testing accuracy surpassing prominent DL models. Figure 2 shows the instant of progression of various DL models from 1998 to 2017.

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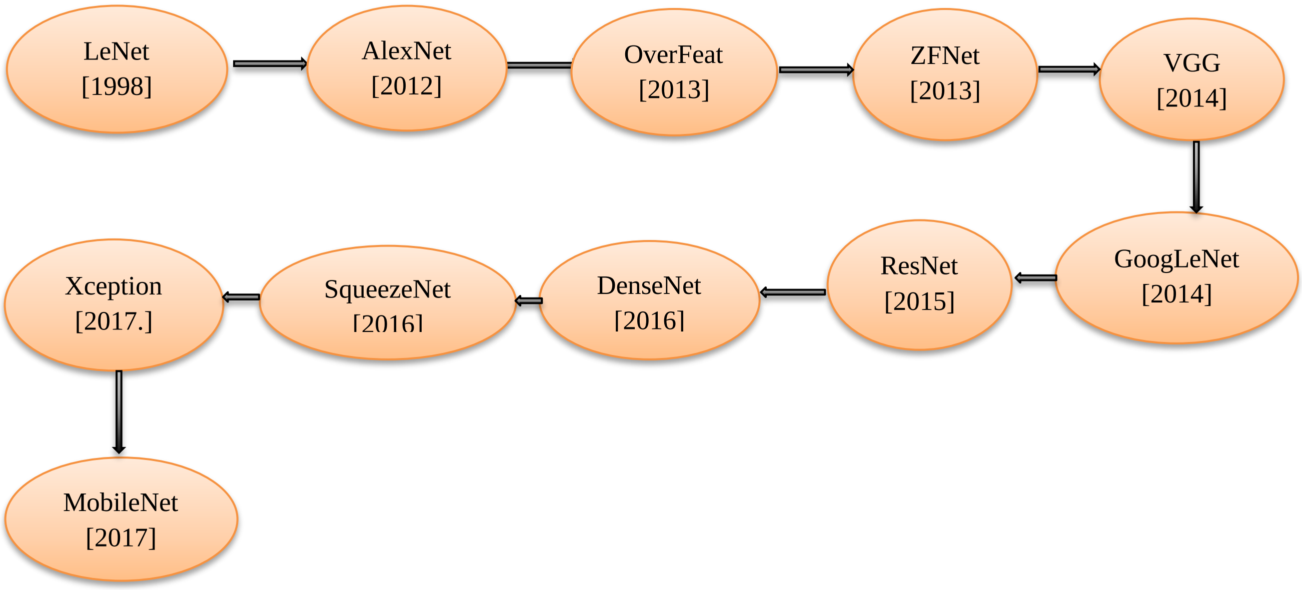

Figure 2. Instant of the progression of various DL models

4. EXECUTION OF DL MODELS

Execution of deep learning (DL) models can be carried out with or without the integration of visualization techniques. Here, we will explore both scenarios: implementing DL models without visualization techniques and implementing DL models with visualization techniques.

With no Visualization Technique:

In this approach, DL models are implemented solely based on their architecture and data processing mechanisms. The focus is primarily on designing and training the neural network architecture to effectively learn patterns and features from input data. While DL models can achieve high levels of accuracy in classifying plant diseases, the lack of visualization techniques can limit our understanding of how the model arrives at its decisions. This can make it challenging to interpret the model's predictions and identify the specific features contributing to its decisions.

The model [13] offers a practical decision support tool that aids farmers in recognizing diseases afflicting banana plants. The process involves capturing an image of a leaf exhibiting symptoms, which is then analyzed by the system to determine the specific disease type. Specifically, they utilized the LeNet architecture. The CNN model [17] was trained using images of healthy and diseased maize leaves using the Neuroph framework. The trained model was able to achieve an accuracy of almost 100% during a test set. It was also evaluated using datasets from the Plant Village website.

The study [18] employs pretrained deep learning models such as AlexNet, GoogLeNet, and ResNet. A comparative analysis of the various networks using Adam and SGD optimization techniques was performed. Furthermore, the impact of batch size and the number of iterations on ResNet's transfer learning performance was evaluated. Interestingly, the study suggests that for this specific task, larger batch sizes and iterations can not necessarily enhance the target model's accuracy. The appropriate settings depend on the dataset and the network in use.

VGG [19] achieved an impressive accuracy of 99.53% (top-1 error of 0.47%) when classifying previously unseen plant leaf images from a testing set. While the system demonstrates a significantly high success rate, it still faces challenges before becoming a comprehensive tool for real-world use. Research conducted a comprehensive comparison between deep feature extraction and transfer learning methodologies for detecting plant diseases and pests. The study [16] encompassed the application of nine powerful deep neural network architectures to both feature extraction and transfer learning scenarios. Deep features were first extracted from the networks using ML classifiers. These were then refined by using images of plants and pests. The study was then compared with the traditional methods. The results of the analysis revealed that the models were 97.9% accurate. The evaluation outcomes demonstrated that deep learning models consistently outperformed traditional approaches. Notably, the results obtained from deep feature extraction surpassed those of transfer learning.

Inception v3 convolutional neural network [5] was used for achieving highly accurate automated cassava disease detection through image recognition. Transfer learning was employed in conjunction with common machine learning methods, with the SVM model demonstrating the highest

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prediction accuracies for four out of six disease classes. According to the results, the SVM model was able to achieve the highest accuracy for red mites damage and cassava mosaic disease when compared to the original dataset. In addition, it was able to perform well for brown leaf spot and healthy plants when compared to the leaflet dataset.

The authors [21] introduced a robust diagnostic system tailored for identifying viral diseases in cucumbers. The system comprehensively addresses a wide spectrum of potential viral diseases affecting cucumbers, while also minimizing restrictions on diagnostic protocols during image capture. Through the use of CNNs, the classifier was able to achieve an average accuracy of 82%. The authors [22] presented an innovative approach that utilizes super-resolution techniques to enhance image-based phenotyping and vigor diagnosis within the agricultural context. A super-resolution method known as SRCNN was initially developed to improve the quality of images depicting various tomato diseases. The results of the study revealed that SRCNN performed better than the standard image scaling techniques in terms of multiple metrics, such as MSE, SSIM, and PSNR. The researchers utilized CNN-based techniques to classify images related to diseases. They were able to achieve better classification accuracy by using super-resolution images instead of low-quality ones. This advancement mitigated certain misclassifications that arose due to visual similarities among diseases when using low-resolution images, showcasing substantial improvement with super-resolution images.

The study [23] focused on diseases that induce observable changes in the physical appearance of tomato plant leaves. These alterations are discernible using RGB cameras. While prior research has utilized standard feature extraction methods to identify diseases in plant leaf images, this study embraced deep learning approaches for enhanced accuracy. A pivotal aspect of the implementation was the selection of a suitable deep learning architecture. The two architectures, SqueezeNet and AlexNet, were evaluated. The training data was collected from the Plant Village dataset, which included various tomato leaf images. By leveraging deep learning and meticulously chosen network architectures, this study endeavors to equip robotic systems with the capability to detect tomato plant diseases swiftly and accurately. Another study [24] was centered on the refinement and assessment of cutting-edge deep CNNs for the classification of plant illnesses based on images. A comprehensive empirical analysis of various deep learning architectures was conducted. The structures that were evaluated included VGG 16 inception V4, ResNet with 151, 101, and 50 layers, and DenseNets with 121 layers, among others. The accuracy of the data collected by the DenseNets system improved as the number of epochs went up. There were no signs of degradation or overfitting, and it performed well even with low computational time and fewer parameters. It also outperformed other systems in terms of testing accuracy.

A deep learning framework was used to classify tomato crop diseases using images collected from PlantVillage [25]. The system was trained using VGG16 net and AlexNet, and it was able to achieve good accuracy. The dataset included 13,262 images. The performance of the models was evaluated by performing experiments that involved varying the number of images, minibatch sizes, and the learning rates. The results of the experiments revealed that the minibatch sizes used in the AlexNet architecture did not provide a clear correlation with accuracy. In contrast, the VGG16 net model performed poorly when it increased the minibatch size. The learning rates for bias and weight were also studied and yielded interesting results. The accuracy rate in AlexNet gradually declined until it reached 30 learning rate. It then increased significantly after that. On the other hand, VGG16 net's accuracy rate dropped after it increased the bias and weight learning rates. When it came to computational load, the AlexNet model performed well with minimal execution time.

Using Visualization Technique:

Using visualization techniques, such as activation maximization, saliency maps, and gradient-based attribution, we can learn more about the inner workings of DL models. This provides insights into the regions of interest that the model focuses on when making classifications. By visualizing these areas, we can gain confidence in the model's decisions and identify potential biases or misinterpretations. Using visualization techniques can also aid in identifying cases where the model could be making incorrect predictions due to factors such as adversarial attacks or noisy input data. Additionally, visualization can help in identifying cases of uncertainty or ambiguity where the model could struggle to confidently classify a disease.

The authors [26] delved into a contemporary approach focused on developing a system capable of detecting and classifying plant diseases. Through an analysis and comparison of prior works centered on deep learning (DL), a noticeable trend emerged wherein two principal CNN architectures, namely AlexNet and GoogleNet, were predominantly employed. The outcomes of evaluation unequivocally highlight the potential for enhancing accuracy through the adoption of novel CNN architectures, such as inceptionV3. Beyond this accuracy advancement, our investigation delved into enhancing the interpretability of deep models via visualization techniques. Introducing the saliency map method, authors ought to precisely identify the afflicted regions of the plant subsequent to disease identification. Remarkably, even though the training images

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possessed weak labels, this visualization technique succeeded in autonomously extracting the affected areas without necessitating expert intervention. Moreover, the resultant visualizations exhibited a high level of precision and clarity, thus serving as a valuable aid for individuals lacking expertise in disease identification to comprehend the nature of the diseases effectively.

Cucumber diseases are typically difficult to identify using conventional methods due to their time-consuming nature and subjectivity. The researchers [27] isolated the symptoms of cucumber diseases from the images captured in real-world field locations. To prevent overfitting, the researchers utilized data augmentation techniques. They then combined these with 14,208 images to create an augmented dataset, which led to a 93.4% accuracy rate. To test the effectiveness of DCNN in identifying cucumber diseases, the authors performed parallel experiments with different types of classifiers. The results of the study revealed that the DCNN system is very accurate in identifying these types of diseases. The findings of this study indicate that deep learning can help improve the efficiency of the field-based disease detection process.

Northern Leaf Blight is a major threat to maize crops, which can cause significant yield losses. Unfortunately, it is difficult to accurately survey vast areas to find NLB lesions. In order to address this issue, the authors [28] developed an automated system that can identify the lesions in images of plants captured from the field. The system was built using a computational pipeline that consists of CNNs. These are trained to identify the NLB lesions in small image regions. The generated heat maps were then inputted into the final CNN, which would then categorize the image based on the presence or absence of the lesions.

Many of these classifiers have been developed using limited datasets, concentrating on extracting hand-crafted features from images for leaf classification. In this study [29], authors have taken a substantial leap forward by utilizing a large dataset, surpassing current standards. For classification task, authors harnessed the power of CNNs as the learning algorithm. To scrutinize the efficacy of our deep model, we employed visualization techniques to comprehend disease symptoms and localize affected regions within the leaves.

Crop diseases [30] pose a significant threat to global agricultural production, leading to substantial economic losses. Monitoring the health of crops is essential to curb disease spread and implement effective management strategies. Our aim with this framework is to provide a thorough overview of wheat disease and its related regions using just annotations at the picture level. With the assistance of the latest Wheat Disease Database 2017, our system achieved an average recognition accuracy of 97.95% and a precision of 95.12%. This framework vastly outperforms its predecessors in terms of CNN performance. These include the VGG-CNN-VD16 and VGG-CNN-S, which had a mean accuracy of 73.00% and 93.27%, respectively. The proposed system not only achieves superior recognition accuracy compared to conventional CNN architectures with the same parameter count but also maintains precise disease area localization.

The recognition of visually interpretable cues in human interactions ensures the practicality of predictions, verifying their usefulness. The presence of these cues can help identify stress levels and types that need attention, which can improve the efficiency of targeted data collection and retraining efforts. In addition, it eliminates the need for complicated rules that involve factors such as shapes, colors, and sizes. The authors [31] of this study talk about the four phases of plant stress phenotype. These include identification, prediction, classification, and quantification. The authors of this study introduce a machine vision-based approach that can be used in the first three phases of plant stress assessment. This method can be widely used in digital agriculture to improve the accuracy and speed of the process. The findings of the study highlight the system's resilience against variations in illumination. The model can be modified based on the collected data from different imaging platforms, such as satellites, drones, and ground-based sensors.Authors foresee the potential for extending this approach beyond plant stresses to other domains, including animal and human diseases, as well as incorporating different imaging modalities like hyperspectral imaging and diverse scales such as ground and aerial perspectives. This holistic expansion holds the promise of advancing sustainable agriculture, food production, and healthcare practices.

DL offers a variety of solutions to problems related to plant pathology. This study aims to develop a novel method for detecting rice diseases using CNNs. The study [32] utilized a dataset comprising of 500 images of both healthy and diseased rice stems and leaves. CNNs were trained to identify 10 prevalent rice diseases. The accuracy rate is higher than that of standard models. The study's simulation results show that the proposed method can identify rice diseases.

Another study [33] is to develop a method that can identify and classify fruit diseases using CCDF. This approach involves two main phases: first, identifying the infected areas, and then extracting and classifying the features. In the first step, a hybrid approach is used to enhance the contrast of the input image. A segmentation technique is then used to separate the infected regions from the background. The second phase of the study involves using deep models known as VGG16 and Caffe AlexNET to extract various features from different fruit diseases. These models are then used to perform a parallel feature fusion procedure. The final step involves using a multi-class SVM to classify the collected features.

A study [34] conducted on a deep learning methodology revealed that it could identify apple leaf diseases in real time using CNNs. Authors introduced an improved approach that utilizes deep CNNs for rapid detection of apple leaf diseases. This framework aims to create a novel model for detecting apple leaf disease by building on the ALDD dataset, which includes complex field images and laboratory images. The model is then equipped with the Rainbow concatenation and GoogLeNet Inception framework to improve its performance. It is specifically designed to identify the various common apple leaf diseases. The results of the experiment revealed that the model was able to achieve a detection rate of 78.80% on the ALDD. This model was able to achieve a fast detection rate of 23.13 FPS. These results demonstrate the model's capability to identify apple leaf diseases at an early stage. It is also more accurate and faster than existing techniques.

Various deep learning models have been harnessed in tandem with visualization techniques to enhance the comprehension of plant diseases in numerous research studies. For instance, in [25], the concept of saliency maps was introduced to visually highlight disease symptoms. In [35], the CałeNet CNN architecture identified 13 distinct plant diseases, achieving an impressive accuracy of 96.30%, surpassing previous approaches like SVM. The research utilized various filters to identify disease spots. It was also able to use the public PlantVillage dataset to build a CNN framework [26]. Comparison of the two renowned CNN architectures revealed GoogLeNet's superior performance. Additionally, visualization activations in the initial layers aptly depicted disease spots. In [36], an adapted LeNet model was employed for detecting olive plant diseases, utilizing segmentation and edge maps to pinpoint disease locations.

A study utilized detectors such as R-FCN, SSD, and Faster-RCNN alongside well-known frameworks, including VGG, AlexNet, and GoogLeNet. The analysis revealed that the optimal configuration was between the ResNet-50 and R-FCN detectors. The addition of bounding boxes also helped improve the identification of diseases [27].

The study [37] aimed to analyze three CNN models for the detection of pests and diseases: the ResNet-V50, Inception-V2 and MobileNet-V1. It utilized different CNN configurations and presented heat maps as input for images of plants infected with the diseases. The study also used ROC curves for the evaluation of the models.

5. FINDINGS AND TRENDS

Reference	Focus	Methodology and Results
13	Banana disease identification	LeNet architecture utilized for classification of banana diseases based on leaf images.
40	Maize leaf disease classification	CNN model trained using Neuroph framework achieves 99.35% accuracy on held-out test set and 92.85% on Plant Village datasets.
4	Tomato leaf disease identification	Transfer learning with Alex Net, GoogLe Net, and Res Net evaluated. ResNet with SGD optimization achieves 96.51% accuracy.
19	Plant disease identification	VGG CNN attains 99.53% accuracy in classifying plant leaf images.
16	Feature extraction vs. Transfer learning	Nine deep neural network architectures compared. ResNet50 with SVM achieves 97.86% accuracy.
5	Cassava disease detection	Inception v3 achieves high accuracies for cassava disease classes, aiding smartphone-assisted diagnosis.
20	Cucumber disease diagnosis	CNN-based approach detects viral diseases in cucumbers, aiding farmers in identifying diseases.
21	Maize disease recognition	CNN model demonstrates 78.80% mAP on Apple Leaf Disease Database, with highest-detection speed of 23.13FPS.
22	Tomato leaf disease detection	RGB camera-based detection of physical changes in tomato plant leaves using deep learning, improving accuracy.

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23	Deep learning architecture assessment	Comparative analysis of various deep learning architectures; DenseNets outperform with 99.75% testing accuracy.
24	Tomato crop disease classification	The VGG16 and AlexNet nets were utilized to classify tomato crop diseases. They achieved an accuracy rate of 97.29% and 97.49%, respectively.
25	Enhancing interpretation	Introduced saliency maps to visualize affected regions in deep models for plant disease identification.
35	Disease classification	Utilized CałeNet CNN architecture to achieve 96.30% accuracy in identifying 13 plant diseases, surpassing SVM.
25	Disease detection	Employed AlexNet and GoogLeNet CNNs, GoogLeNet outperformed, visualized activations in initial layers for disease spots.
36	Olive disease detection	Adapted LeNet model for olive plant diseases, incorporated segmentation and edge maps for disease location.
41	Cucumber disease classification	Compared Random Forest, SVM, and AlexNet models, implemented image segmentation methods to observe disease symptoms.
42	Teacher/student network	Introduced a novel DL model for disease identification with unique visualization approach.
27	Plant disease detection	The combination of R-FCN and ResNet-50 with DL models like VGG, Alex Net, and GoogLe Net is ideal.
37	Banana disease and pest detection	Through the various CNN models, including the ResNet-50, Inception-V2, and MobileNet-V1, we were able to identify the banana disease.
28	Visualizing deep models	Employed various CNN combinations, presented heat maps for disease identification, incorporated ROC curves and feature maps for rice disease.
38	Hotspot technique	Utilized an algorithm for hotspot extraction via image segmentation modification for color constancy in disease detection.
39	Cucumber disease detection	Employed dilation convolutional neural network for identifying cucumber plant diseases.

6. CHALLENGES AND FUTURESCOPE

The use of deep learning to identify and classify plant diseases has shown promising results. But there are still many challenges that need to be resolved and new directions explored.

Challenges:

- Limited Data Availability: An ongoing challenge is the availability of large and diverse datasets for training deep learning models. Building models that are robust and generalized requires collecting data on a wide variety of plant species, environmental conditions, and diseases.
- Annotation Effort: Manually annotating large datasets for plant diseases can be time-consuming and prone to errors. Developing semi-supervised or weakly supervised learning methods to reduce the annotation burden is an area of interest.
- Interclass Variability: Some plant diseases can exhibit variations due to factors like growth stage, lighting conditions, and overlapping symptoms. Designing models that can handle these variations and still make accurate predictions is a challenge.
- Small-Scale Farming: The majority of farmers are small-scale growers who could lack resources for high-end imaging equipment or computational infrastructure. Developing lightweight models that can run on low-resource devices and still provide accurate results is crucial.
- Model Interpretability: Deep learning models often lack interpretability, making it difficult to understand the basis of their predictions. Developing techniques for explaining model decisions and highlighting relevant image regions can enhance model trustworthiness.

Future Research Directions:

- Zero-shot and few-shot learning are methods that enable the recognition and classification of new plant diseases. This field is currently under exploration.
- Transfer Learning Across Crops: Extending transfer learning techniques to transfer knowledge across different crops can help in building accurate disease detection models for less-studied crops.
- Multimodal Fusion: Integrating information from multiple sources, such as images, spectral data, and environmental sensors, can improve the accuracy and robustness of disease detection models.
- Spatiotemporal Analysis: Incorporating spatial and temporal information from images taken at different time points can enhance disease prediction accuracy and facilitate early detection.
- Uncertainty Estimation: Developing methods to quantify uncertainty in model predictions can help in decision-making and improve the reliability of disease detection systems.
- Active Learning: Exploring active learning strategies to select the most informative samples for annotation can help in optimizing the data labeling process and improving model performance.
- Edge Computing: Designing models that can perform inference on edge devices (e.g., smartphones, drones) can enable real-time disease detection directly in the field.
- Real-World Deployment: Validating and deploying deep learning models in real-world agricultural settings and assessing their impact on disease management practices is a critical direction for practical implementation.
- Collaboration with Domain Experts: Collaboration between machine learning researchers and domain experts, such as plant pathologists and agronomists, is essential for developing effective disease detection solutions that address practical challenges.

7. CONCLUSIONS

In conclusion, the use of deep learning techniques for plant disease detection and classification holds significant promise and potential for revolutionizing agricultural practices. Through extensive research and experimentation, it has been demonstrated that deep learning models can effectively leverage their capacity to learn intricate patterns and features from complex image data, enabling accurate and efficient identification of various plant diseases. The widespread adoption of CNNs has demonstrated their ability to perform well in the domain of disease classification. These models can automatically extract various features from images, which eliminates the need for manual engineering. Several architectures, such as the VGG, Inception, and AlexNet, have been used to achieve high-level accuracy in this area.

Furthermore, the integration of transfer learning has proven to be a valuable strategy. By leveraging pre-trained models on large-scale datasets, the training process becomes more efficient and effective, especially when faced with limited labeled data for specific plant diseases. Fine-tuning these pre-trained models for disease detection showcases how domain-specific knowledge can be merged with general visual recognition capabilities, enhancing overall performance. However, challenges persist, such as the scarcity of annotated data, class imbalances, and the potential for model biases. Plant diseases' increasing complexity and the need to enhance deep learning models' performance in detecting them are crucial issues that need attention to improve their effectiveness. Additionally, the need for interpretable and transparent models has led to the integration of visualization techniques, aiding researchers, and practitioners in comprehending how these intricate models make predictions.

The development of deep learning systems for plant classification and disease detection has become a multidisciplinary field that requires collaboration among various experts. This can be done through the establishment of collaborations between machine learning researchers and agricultural experts. The development of advanced models and techniques, as well as the use of new technologies such as the Internet of Things, will help improve the detection of plant diseases. This will allow for more effective and sustainable practices.

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