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A Survey on Plant Diseases Detection Using Deep Learning Techniques

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Abstract:

Plant diseases pose a significant threat to global agricultural productivity, leading to substantial economic losses and food insecurity. Traditional methods for disease detection, which rely on manual observation and expert consultation, are often time-consuming, error-prone, and inefficient for large-scale monitoring. Recent advancements in deep learning have shown tremendous potential in automating plant disease detection with high accuracy and scalability. This survey presents a comprehensive analysis of deep learning techniques applied to plant disease identification through image classification, segmentation, and feature extraction. Various architectures, including Convolutional Neural Networks (CNNs), Residual Networks (ResNets), VGGNet, and newer attention-based models, are explored for their effectiveness in diagnosing diseases from leaf images. Publicly available datasets, performance metrics, and preprocessing methods are discussed to evaluate model robustness and generalization. The study also addresses challenges such as data imbalance, model interpretability, and real-time deployment constraints in field environments. Finally, it highlights future research directions aimed at enhancing model accuracy, scalability, and integration into precision agriculture systems for proactive crop management.

Keywords—Deep Learning,Agriculture, Plant, Disease, Farmers, Crop

I. Introduction

Agriculture is a critical pillar of global food security, with crop health playing a pivotal role in determining yield quality and quantity. However, plant diseases remain one of the most persistent and damaging challenges in modern agriculture. These diseases, caused by pathogens such as fungi, bacteria, viruses, and pests, can significantly reduce crop productivity and quality if not identified and treated early. Traditionally, plant disease detection has relied on manual inspection by farmers or agricultural experts. While effective in some scenarios, these conventional methods are often labor-intensive, subjective, time-consuming, and prone to human error, especially in large-scale or remote farming environments.In recent years, advancements in artificial intelligence (AI), particularly deep learning, have opened new possibilities for automating plant disease detection. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown exceptional performance in image recognition tasks, making them highly suitable for analyzing plant leaf images to identify disease symptoms. These models can automatically learn features from large datasets, reducing the need for manual feature engineering and improving classification accuracy [2].

The integration of deep learning into agriculture enables faster, more accurate, and scalable solutions for disease identification. Numerous studies have demonstrated that deep learning approaches can achieve high accuracy in detecting a wide variety of plant diseases across multiple crop types, including wheat, rice, maize, tomato, and potato. Furthermore, the use of transfer learning, data augmentation, and ensemble models has significantly enhanced model performance, even when trained on relatively small or imbalanced datasets.Despite these promising developments, several challenges remain. These include the scarcity of high-quality annotated datasets, variations in environmental conditions (such as lighting and background noise), and the need for real-time, field-ready deployment on mobile or embedded devices. Moreover, model interpretability and the ability to explain decisions to farmers and stakeholders are crucial for building trust in AI-driven solutions. This survey aims to provide a comprehensive overview of current deep learning techniques used for plant disease detection. It reviews various architectures, datasets, performance metrics, and real-world applications. The study also identifies the limitations of existing methods and suggests future research directions to improve accuracy, usability, and scalability. By doing so, this survey contributes to the growing body of work focused on integrating deep learning into sustainable and precision agriculture practices, ensuring timely disease management and increased crop productivity.

II. LITRETURE REVIEW

Recent studies have demonstrated the efficacy of machine learning in soil fertility prediction and crop recommendation. Algorithms such as Random Forest, Decision Trees, and Support Vector Machines have been widely applied to analyze soil parameters like pH, NPK levels, and moisture content. Researchers highlight improved accuracy and efficiency compared to traditional methods. Several works emphasize real-time data integration from sensors, enabling site-specific recommendations. However, challenges like data quality, regional generalization, and model interpretability remain areas of ongoing research and development.

Authors [1] utilizes deep learning to enhance kiwifruit diseaseidentification by evaluating eight advanced convolutional neural network (CNN) architectures on real-worldfield data. Among these, ShuffleNet_V2_x0_5 proved to be the most effective model. By incorporatingadvanced optimization strategies, including the AdamW optimizer and OneCycleLR scheduler, the modeldemonstrated rapid convergence and robust performance, achieving over 99% accuracy within fiveepochs, with only 1.37M parameters and 0.04G FLOPs. The lightweight architecture and computationalefficiency make it particularly suitable for resource-limited settings, including mobile and embeddedplatforms. These findings underscore the utility of ShuffleNet_V2_x0_5 in supporting scalable andefficient disease management within precision kiwifruit agriculture.

Author's [2] focuses on introducing MangoLeafXNet,a customized Convolutional Neural Network (CNN) architecture specifically tailored for the classificationof mango leaf diseases, along with a healthy class. Authors proposed model comprises six layers optimizedto capture intricate disease patterns, demonstrating superior performance compared with prevalent pretrained models. The model is trained and evaluated on three publicly available datasets: MangoLeafBD(4000 images across 8 classes), MangoPest (16 pest classes including healthy leaves), and MLDID (3000) high-resolution images across 5 classes). Our model demonstrated exceptional classification performance,attaining 99.8% accuracy, 99.62% recall, 99.5% precision, and an F1-score of 99.56%. Further validation onthe MangoPest dataset and the Mango Leaf Disease Identification Dataset (MLDID) resulted in accuraciesof 96.31% and 96.33%, respectively, confirming the robustness and adaptability of MangoLeafXNet acrossdifferent datasets. Additionally, we incorporate Explainable AI techniques, including GRAD-CAM, SaliencyMap, and LIME to enhance the interpretability of our model. Author's deployed Gradio web interface to createan interactive interface that allows users to upload images of mango leaves and get real-time classificationand validation results along with confidence scores. This contribution not only advances the state-of-the-artin mango leaf disease classification but also offers promising prospects for real-time disease diagnosis andprecision agriculture applications, contributing to enhanced crop health monitoring and sustainable mangocultivation practices.

Author's [3] examined CNN, VGG-16, VGG-19 and ResNet-50 models on plant-village10000 image dataset to detect crop infection and got the accuracy rate of 98.60%, 92.39%, 96.15%, and98.98% for CNN, VGG-16, VGG-19 and ResNet-50 respectively. This work indicates that ResNet-50 outperformsthe other models with an accuracy of 98.98%. So, the ResNet50 model was chosen to be developed into a smartweb application for real-life crop disease prediction. The proposed web application aims to assist farmers inidentifying diseases of plants by analyzing photos of the plant leaves. The proposed application uses theResNet50 transfer learning model at its heart to distinguish healthy and infected leaves and classify the presentdisease type. The goal is to help farmers save resources and prevent economic loss by detecting plant diseasesearly and applying the appropriate treatment.

Authors [4] present the current trends and challenges for the detectionof plant leaf disease using deep learning and advanced imaging techniques. We hope that this work will bea valuable resource for researchers who study the detection of plant diseases and insect pests. At the sametime, we also discussed some of the current challenges and problems that need to be resolved.

Authors [5] model hasthe potential to apply to smart farming of Solanaceae crops and will be widely used by adding morevarious crops as training dataset.construction of a stepwise disease detection model usingimages of diseased-healthy plant pairs and a CNN algorithm consisting of five pre-trained models.The disease detection model consists of three step classification models, crop classification, diseasedetection, and disease classification. The 'unknown' is added into categories to generalize themodel for wide application. In the validation test, the disease detection model classified crops anddisease types with high accuracy (97.09%). The low accuracy of non-model crops was improved byadding these crops to the training dataset implicating expendability of the model.

III. FINDINGS OF THE SURVEY

The survey on plant disease detection using deep learning techniques reveals significant advancements in automating agricultural diagnostics and improving crop health monitoring. Several key findings emerged from the review of current literature and technological developments:

1. Superior Accuracy of Deep Learning Models:

Deep learning, particularly Convolutional Neural Networks (CNNs), has consistently demonstrated high accuracy in identifying plant diseases from leaf images. Models such as AlexNet, VGGNet, ResNet, Inception, and EfficientNet have been effectively used for classifying diseases across various crops. When trained on well-annotated datasets, many of these models achieve classification accuracies exceeding 95%, outperforming traditional machine learning approaches.

2. Public Datasets and Data Augmentation:

The availability of publicly accessible image datasets, such as PlantVillage, has significantly accelerated research in this area. However, the survey finds that data scarcity and class imbalance remain prevalent issues. To address this, data augmentation techniques (rotation, zooming, flipping) and synthetic image generation using GANs are commonly used to improve model generalization.

3. Importance of Transfer Learning:

Transfer learning has emerged as a powerful method to overcome limited dataset challenges. Pretrained models on large datasets like ImageNet are fine-tuned to specific plant disease datasets, reducing training time and improving performance, particularly in small-scale or resource-limited agricultural settings.

4. Mobile and Real-Time Applications:

Recent research has focused on deploying deep learning models on mobile devices and edge computing platforms for real-time field applications. Lightweight CNN architectures like MobileNet and quantized versions of existing models are showing promise for on-device disease diagnosis.

5. Challenges in Field Deployment:

Despite technical progress, practical implementation faces challenges such as varying lighting conditions, background noise, image quality, and leaf occlusions in real environments. Additionally, farmers' lack of access to digital infrastructure and the need for user-friendly interfaces are barriers to widespread adoption.

Finally, deep learning offers a robust and scalable solution for plant disease detection. While the technology has shown great promise in research settings, bridging the gap between lab performance and real-world usability remains a critical area for future work.

IV. CONCLUSION

The survey underscores the transformative potential of deep learning techniques in plant disease detection, offering a scalable, accurate, and automated approach to agricultural diagnostics. Convolutional Neural Networks (CNNs) and their variants have shown remarkable success in classifying plant diseases from leaf images, significantly outperforming traditional methods in terms of precision and efficiency. With the integration of transfer learning and data augmentation, deep learning models are becoming increasingly adaptable to diverse agricultural contexts, even in cases of limited or imbalanced datasets.Moreover, the emergence of lightweight architectures and mobile-compatible models is paving the way for real-time, field-level disease monitoring, making deep learning solutions accessible to farmers and agronomists globally. However, several challenges persist—such as variability in real-world environmental conditions, limited access to high-quality labeled data, and technological adoption barriers in rural communities. To bridge these gaps, future research must focus on creating diverse, annotated datasets, improving model robustness under field conditions, and developing user-friendly applications tailored for end-users. Ultimately, the integration of deep learning into plant disease management can enhance early detection, reduce crop loss, and promote sustainable agricultural practices, making it a vital tool for modern farming in the face of increasing global food demand.

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