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Plant Disease Detection and Classification by Deep Learning: A Review of Literature

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Abstract: Deep Neural network has revolutionized pattern recognition using image data. Its application to life sciences has proven to be a great tool. Using various approaches to recognize patterns within images, it has been possible to create automatic system to analyse plant health and diseases at an exponential pace. This paper reviews the recent progress in this field.
Keywords: Plants, Disease, Deep Learning, Artificial Neural network.

I. INTRODUCTION

Plant diseases pose significant threats to agricultural productivity, food security, and environmental sustainability worldwide. Early detection and accurate classification of these diseases are critical for effective disease management and mitigation strategies. Traditional methods of disease detection often rely on visual inspection by trained experts, which can be time-consuming, labor-intensive, and prone to subjective biases. Moreover, the increasing global demand for food necessitates innovative and efficient approaches to address these challenges.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized various fields, including computer vision and pattern recognition. Deep learning techniques offer promising opportunities to automate and enhance the process of plant disease detection and classification. By leveraging large-scale datasets and powerful computational resources, deep learning models can learn intricate patterns and features from images, enabling accurate and rapid identification of diseased plants.

In this context, numerous studies have investigated the application of deep learning for plant disease detection and classification. These studies have explored various aspects, such as transfer learning, network architectures, and image preprocessing techniques, to optimize the performance of deep learning models in agricultural settings. By analyzing diverse datasets encompassing a wide range of plant species and disease types, researchers have evaluated the efficacy of deep learning algorithms in detecting and classifying plant diseases with high accuracy and efficiency.

However, despite the progress made in this field, several challenges remain. Limited availability of annotated datasets, domain-specific variations in imaging conditions, and the need for real-time deployment in agricultural environments pose significant obstacles to the widespread adoption of deep learning-based approaches for plant disease detection. Addressing these challenges requires interdisciplinary collaboration among researchers, agronomists, and technologists to develop robust and scalable solutions.

In this paper, we present a comprehensive review and analysis of recent research on plant disease detection and classification using deep learning techniques. We examine the methodologies, findings, and implications of existing studies, with a focus on identifying key trends, challenges, and opportunities in this rapidly evolving field. By synthesizing the collective knowledge and insights from these studies, we aim to provide valuable guidance for future research directions and practical applications in plant pathology and precision agriculture.

II. REVIEW OF LITERATURE

A paper describing [1] deep learning (DL) approaches found that for plant disease detection and summarized various visualization techniques for symptom recognition. Despite recent progress, several research gaps persist. Firstly, while many studies use the PlantVillage dataset for evaluation, its simple background doesn't reflect real-world environments. Incorporating hyperspectral/multispectral imaging with efficient DL architectures could enable early disease detection. Additionally, there's a need for more effective visualization methods to pinpoint disease spots and reduce unnecessary pesticide use. DL models should be enhanced to detect diseases throughout their entire lifecycle and adapt to various illumination conditions. A comprehensive investigation into factors affecting disease detection, such as dataset characteristics and learning rates, is warranted. The paper [2] introduces convolutional neural network models for plant disease detection and diagnosis using simple leaf images of healthy and diseased plants.

Training utilized a database of 87,848 images, spanning 25 different plants across 58 distinct [plant, disease] combinations, including healthy plants. Multiple model architectures were trained, achieving a remarkable 99.53% success rate in identifying the corresponding [plant, disease] combination or healthy plant. This high accuracy suggests the model's potential as an advisory or early warning tool and could be expanded to support an integrated plant disease identification system for real cultivation conditions. While some paper including [3] discussed the significant advancements made in object recognition and image classification through convolutional neural networks (CNNs) in recent years, surpassing traditional approaches reliant on hand-engineered features. While prior methods required complex feature engineering and were limited in their adaptability to changing datasets, CNNs offer a more scalable and efficient solution. The authors presented a novel approach inspired by Krizhevsky et al. (2012), demonstrating the effectiveness of end-to-end supervised training for image classification tasks, particularly in plant disease identification. Their method involves training a CNN model on a dataset containing over 54,000 images of plant leaves representing various crop species and disease conditions. Remarkably, the model achieves an accuracy of 99.35% in classifying both crop species and disease presence across 38 classes. Despite this success, the authors acknowledged limitations such as reduced accuracy when tested on diverse image conditions and constraints in classifying images beyond single leaves with homogeneous backgrounds.

Future efforts are directed towards improving model robustness with more diverse training data and enhancing classification capabilities to accommodate real-world scenarios where diseases manifest on various plant parts. While the proposed approach complements existing diagnostic methods, such as laboratory tests, its integration with smartphones presents a promising tool for widespread disease monitoring, particularly in regions with limited access to traditional diagnostic resources. The authors anticipate further advancements in mobile technology to enhance diagnostic accuracy through additional sensor data and improved algorithms in the near future.

Another study [4] focuses on leveraging deep learning techniques, particularly deep convolutional neural networks (CNNs), for image-based plant disease classification, aiming for a fast, automatic, and accurate system. The authors conduct empirical comparisons of several state-of-the-art CNN architectures, including VGG 16, Inception V4, ResNet with varying depths (50, 101, and 152 layers), and DenseNets with 121 layers. They use a dataset comprising 38 classes of diseased and healthy leaf images from 14 plant species sourced from PlantVillage. The primary objective is to develop efficient models for plant disease identification to enable early and accurate interventions, thus addressing food security challenges. The experiments reveal that DenseNets exhibit a consistent improvement in accuracy with increasing epochs, without signs of overfitting or performance degradation. Additionally, DenseNets require fewer parameters and reasonable computing time to achieve state-of-the-art performance, outperforming other architectures with a testing accuracy score of 99.75%. The training of the architectures is performed using Keras with Theano backend. Overall, the study underscores the effectiveness of DenseNets in achieving high accuracy for plant disease classification, highlighting their potential for practical applications in agricultural management and food security initiatives.

The study [5] highlights the importance of automated plant disease recognition tools in aiding decision-making in agriculture, especially where technical support is limited. While deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown promise, previous studies often relied on limited and homogeneous datasets, such as the PlantVillage database. To address this, the study introduces a more diverse dataset, including 79 diseases affecting 14 plant species, captured under various conditions. Despite its qualitative representation, the dataset lacked in quantity, prompting manual segmentation into individual lesions and spots, resulting in a larger dataset of 46,409 images. The study employed a pretrained CNN based on the GoogLeNet architecture, achieving accuracies ranging from 75% to 100% across different crops. Results indicated higher overall accuracy (94%) using individual lesions and spots compared to original images. Classification experiments demonstrated consistent improvements, particularly with the use of localized images. The study emphasizes the need for a substantial number and variety of images for reliable CNN training. While the creation of the expanded dataset was labor-intensive, the approach of using localized images mitigated this issue. In conclusion, while CNNs show promise in plant disease classification, dataset limitations hinder the emergence of comprehensive systems. Efforts toward building more representative datasets are essential for advancing automated plant disease recognition systems.

The paper [6] emphasizes the significance of automated tools in detecting and recognizing plant diseases due to limitations in human-based visual inspection, especially in areas lacking trained plant pathologists. While conventional machine learning techniques have shown promise, the advent of deep learning, particularly Convolutional Neural Networks (CNNs), has garnered increasing attention since 2015. However, many studies employ similar tools and datasets, resulting in limited variation in reported results, and practical field conditions often pose challenges overlooked in research. This article aims to analyze the factors affecting deep learning-based tools for plant disease recognition under realistic conditions, providing guidelines for more thorough investigations.

The factors are derived from experiments using CNNs, with misclassifications carefully analyzed to identify causal factors. The absolute accuracies of the models are deemed less important than understanding the underlying causes of errors. The database used in the experiments contains nearly 50,000 images of various plant diseases and is made freely available for academic purposes. The method describes the database, focusing on images of corn diseases due to their diversity and sufficient quantity. The deep learning approach offers advantages, particularly in symptom recognition. The results show that while absolute accuracies are considered secondary, relative differences between trained neural networks provide insights into factors affecting CNN effectiveness for disease recognition. The table displays accuracies obtained using each trained CNN, including images generated through augmentation techniques.

The study [7] compares fluorescence imaging and thermal imaging for detecting and quantifying apple scab, a plant disease. It demonstrates the superiority of thermal imaging over fluorescence imaging in detecting and quantifying apple scab on leaf surfaces, particularly in practical environmental conditions. The comparison is conducted using statistical methods such as the Neyman–Pearson strategy with the Bhattacharrya distance and ROC curves. Additionally, a linear relationship is established between visually estimated diseased leaf area and imaging-based segmentation of leaf area. These findings suggest the potential of thermal imaging for quantifying the pathogenicity of apple scab and provide a framework for comparing nonconventional optical imaging techniques in plant pathology.

The study [8] investigates and compares the performance of various transfer learning mechanisms based on different pre-training tasks and network architectures. Specifically, it explores the impact of pre-training with plant specialized tasks versus general object domain tasks on VGG16, GoogLeNetBN, and InceptionV3 architectures. The study finds that pre-training with plant specialized tasks can reduce overfitting for the deeper Inception-based model, while the VGG16 model with ImageNet pre-training demonstrates better generalization in adapting to new data.

The superiority of VGG16 over Inception-based models is attributed to the limited diversity in the plant disease dataset, which constrains the deployment of deeper architectures. However, the paper suggests that moving towards a broader and more diversified plant disease database, without relying on pre-training models like ImageNet, could enhance model performance. Additionally, to better adapt models to large-scale crops, datasets captured under real cultivation conditions are needed. Furthermore, the paper explores the learned characteristics of the models through visualization of activations, revealing that CNNs trained on crop-disease terminology may not always focus on disease regions but on crop-specific characteristics like leaf venation. To address this, the paper proposes training models based on common disease names rather than specific crop-disease pairs, showing experimentally that such models are more generalizable, especially for new data in different domains and unseen crops.

A study on [9] reveal that blight and wilt are the most extensively researched disease types, with more than 10 disease types covered in a single study. Fungi-related diseases account for 64% of the diseases studied using drones, indicating a significant focus in research. However, viruses, nematodes, and abiotic factors are only studied in 10% of cases, suggesting potential for further research in these areas. Grape and watermelon diseases have received considerable attention, while diseases in kiwi, squash, pear, lemon, onion, and rice have been less explored, indicating potential for drone applications in these crops. Classification tasks are the most common application of drones in disease detection, with field images being the most utilized (58%), followed by plant images (28%) and leaf images (14%). The preference for convolutional neural networks (CNNs) as the primary algorithm may stem from their ability to handle complex deep learning models and the prevalent representation of problems as classification tasks. However, alternative algorithms may be more suitable for different problem representations.

III.CONCLUSIONS

As we have seen , there have been remarkable improvements in plant disease identification using deep learning. The deep learning methods has provided different approaches to use image based machine learning systems to monitor and analyses different plants and their diseases.

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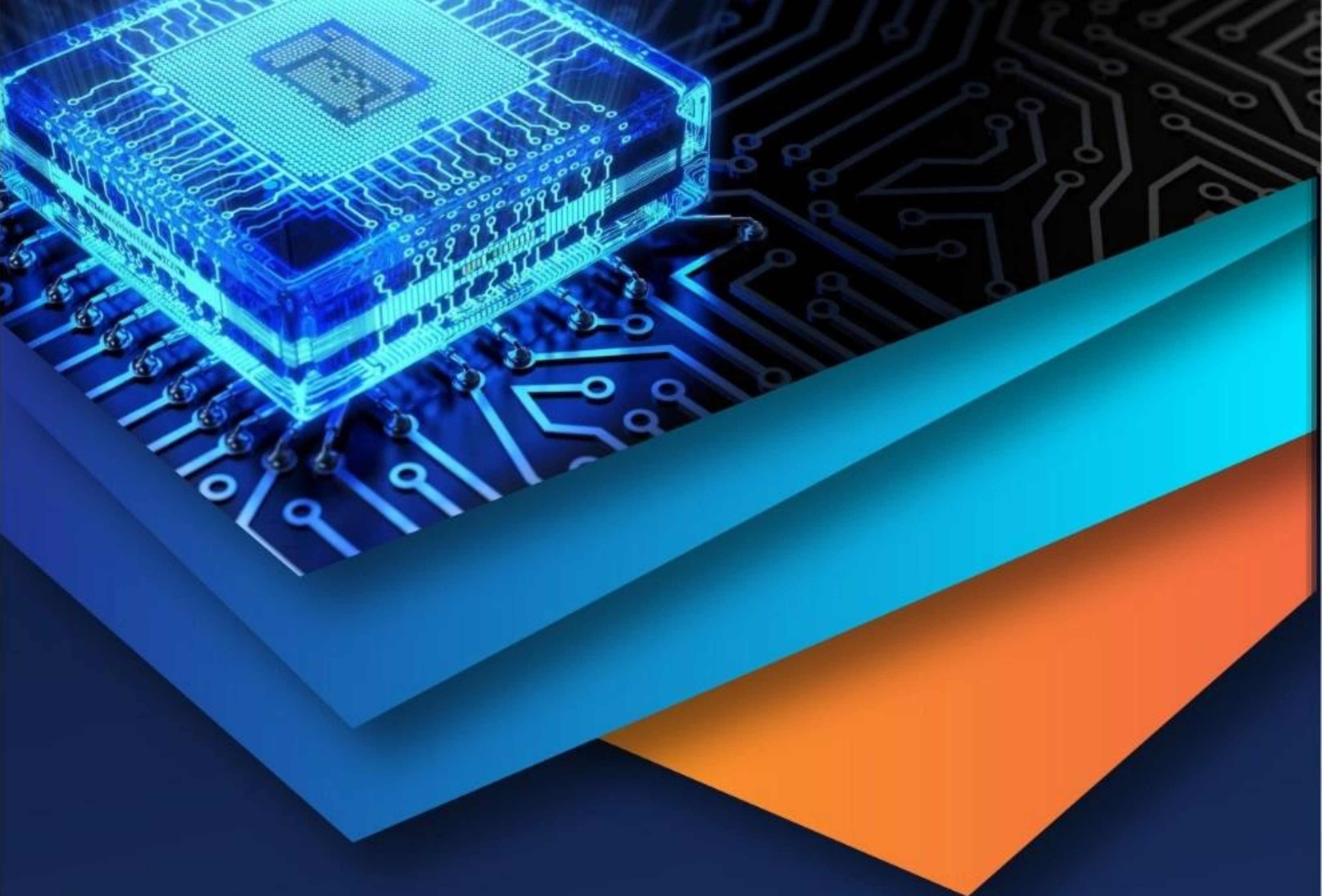

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