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A Review of Plant Disease Identification using Computational Techniques

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***Abstract*—** In India, the imperative to bolster agricultural productivity in the face of population growth and heightened food demands underscores the significance of disease detection in crops. This study delves into advanced plant disease detection methodologies, specifically emphasizing the integration of ML and DL techniques. Machine learning, with its capacity for autonomous information processing, proves instrumental in precise disease identification. However, recent strides in deep learning, particularly in computer vision, reveal superior performance in detecting diverse plant diseases across various crops compared to traditional machine learning. The research advocates for the proactive use of deep learning for early disease detection through image analysis, offering a sentinel approach against bacterial, viral, and fungal infections. This not only fortifies plant disease detection but also charts a course towards sustainable agriculture. The study contributes actionable insights, envisioning a future where technological interventions harmonize with traditional farming practices, fostering resilience and optimizing crop yields to fulfill the evolving requirements of a growing populace.

Keywords— ***Plant Disease, CNN, Computational Techniques, Deep Neural Network, Classification***

I. Introduction

The economic progress of a nation is intricately linked to the prosperity of its agricultural endeavors and resultant productivity. Indeed, the very sustenance of humanity is intimately connected to the reliance on agriculture. Farmers engage in the cultivation of diverse crops, guided by considerations of soil fertility and the resources at their disposal. Nevertheless, fluctuations in climate, encompassing alterations in rainfall patterns, temperatures, and other contributing factors, serve to exacerbate susceptibilities to infections within soils or plants.

The timely recognition of plants and their associated diseases constitutes a pivotal realm of research. In India, a developing nation where a substantial majority of the populace is reliant on agriculture, the significance of this research is heightened. Agriculture plays a central role in ensuring food security, with 75% of the population deriving their livelihood from this sector [1]. As the ultimate source of sustenance, plants not only contribute to the vital aspect of nourishment but also find extensive applications in medicine and various allied industries. Acknowledged as a fundamental component in the ecosystems sustaining both human beings and other living species on Earth, the imperative arises for an automated identification system encompassing not only the classification of plant species but also a comprehensive understanding of their medicinal benefits.

Plant diseases are caused by a variety of pathogens, including bacteria, fungus, and viruses. Plant disease is identified via observable symptoms. These symptoms encompass detectable alterations in the plant's color, shape, or functionality as it reacts to the influence of the pathogen. Figure 1 outlines several prevalent plant diseases and their associated manifestations.

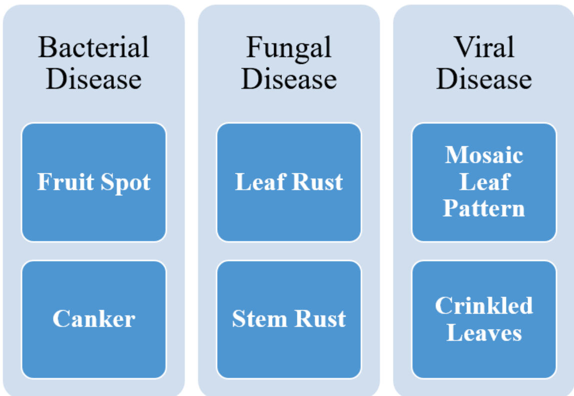

Figure 1 Different Types of Plant Leaf Diseases

In most of the developing countries, agriculture undeniably stands as the predominant source of livelihood and constitutes a substantial proportion of the Gross Domestic Product (GDP). Analogous to human beings, plants are susceptible to various diseases, detrimentally affecting both the quality and quantity of crops. The repercussions of plant diseases on crop productivity are profound [2]. A study conducted by the Associated Chambers of Commerce and Industry of India reveals that annual crop losses attributable to pests and diseases amount to a considerable (500 billion). This figure assumes significance in a nation where a substantial 200 million individuals retire to bed each night with hunger as their companion.

The significance of plant science is emphasized by its crucial role in tackling issues encountered by major agricultural sectors, such as India's notable cotton production. As the second-largest global producer of cotton, India relies on plant science to thwart insect infestations, ensuring the sustained production and high quality of cotton. Notably, India ventured into biotechnology in agriculture in

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2002 by introducing insect-resistant cotton varieties, safeguarding crops from specific pests that pose a threat to cotton cultivation [3].

The expeditious identification of diseases is imperative for preserving the quality and quantity of crops. Despite the cultivation of an extensive array of crop varieties, agriculturalists and pathologists may encounter challenges in visually discerning diseases affecting plants. Particularly in rural areas of developing nations, visualization remains the main modality for disease identification, often necessitating continuous monitoring by experts. However, this approach is not without drawbacks, as it compels farmers in remote regions to undertake arduous journeys for consultations, incurring both time and financial expenses [4]. To ameliorate these challenges, automated computational systems for the detection and diagnosis of plant diseases offer a promising solution, aiding agronomists with their efficiency and precision in high-throughput processes.

Presently, there is a discernible maturation and progression in agricultural technology, marked by the rapid emergence of novel applications and software designed to enhance the daily operations of agricultural producers [5].

One of the burgeoning methodologies, gaining prominence, is the application of machine learning—a facet intricately tied to the broader domain of artificial intelligence. The noteworthy advantages inherent in applications employing this methodology lie in their capability to autonomously identify behavioral patterns in specific agronomic factors. Furthermore, these applications prove instrumental in prognosticating future agronomic trends. Machine learning, situated within the realm of artificial intelligence, involves the study of machines utilizing algorithms that inherently enhance their performance through experiential learning. In practical terms, this entails the development of software adept at optimizing performance criteria through rigorous data analysis.

II. REVIEW STUDIES

The manifestation of plant diseases and the presence of pests stand as pivotal determinants influencing the yield and quality of cultivated plants. Consequently, the early detection of plant diseases assumes paramount significance, aiming to facilitate timely intervention and mitigate adverse effects on productivity. In contemporary agricultural discourse, deep learning has emerged as a transformative force, ushering in breakthroughs for sustainable agriculture. Its applications extend to precision farming, crop protection, water management, and various other domains, showcasing its potential to revolutionize traditional farming practices.

This section undertakes a meticulous exploration through an extensive survey of existing literature, delving into the classification and prediction of plant diseases. The focus of this inquiry encompasses the utilization of both Machine Learning and Deep Learning techniques. By scrutinizing the amalgamation of scientific knowledge and technological innovation in this domain, this survey aims to contribute to the burgeoning field of plant disease detection. The synthesis of insights from diverse sources establishes a comprehensive foundation for understanding the intricacies of disease classification and prediction, thereby paving the way for enhanced agricultural practices and sustainable crop management.

Binnar et al. [6] worked together to create Convolutional Neural Network (CNN) models that utilise deep learning techniques to identify and diagnose plant leaf diseases. The work employed three different models, namely AlexNet, MobileNet, and Inception-v3, to identify diseases in plant leaves. These models were trained and tested using a dataset that included new plant diseases. Furthermore, the trained models were utilised to analyse plant leaf photos obtained from the Internet. Upon evaluation, it was found that the MobileNet model was highly suitable for the new plant diseases dataset. It achieved training and validation accuracies of 99.07% and 97.52% respectively, surpassing the performance of the other models in the study.

Sangeetha R et al. [7] developed a Convolutional Neural Network (CNN) model to predict the health of tomato leaves in relation to illnesses. The model's architecture consisted of four convolution layers, a max-pooling layer, and a subsequent dense layer. The main goal of the model was to categorise tomato leaf conditions into three unique groups: two classes for leaves damaged by disease and one for leaves considered healthy. The conclusion of their endeavours led to the attainment of a remarkable level of precision, peaking at 94.66%. This study highlights the effectiveness of the CNN model in accurately identifying and classifying the health condition of tomato leaves. This contributes to the progress in methods for detecting plant diseases.

Kyamelia Roy et al. [2] introduced an innovative approach to detect Tomato leaf diseases employing DNN. Their approach combines a traditional ML model, PCA with a customised DNN called PCA DeepNet. In addition, the system includes a GAN to guarantee a varied and extensive dataset. The identification process is performed using the F-RCNN algorithm. The thorough assessment of their work resulted in an outstanding classification success rate of 99.60% and an average precision of 98.55%. This work demonstrates the efficacy of the PCA DeepNet model in combination with advanced approaches, exhibiting a significant improvement in the accuracy and precision of Tomato leaf disease detection.

Sinan and Nese [8] endeavored to classify olive leaf diseases through the development of a model utilizing a dataset comprising 3400 olive leaf samples afflicted by Aculusolearius and peacock spot disease. Their study involved a comparative analysis, pitting their proposed model against established VGG16 and VGG19 architectures, using both augmented and non-augmented datasets. The augmented dataset notably achieved the highest success rate, reaching an impressive 95%. This accomplishment was realized through the implementation of various optimization algorithms, including Adam, Adagrad, SGD, and RMSProp.

Marriam Nawaz et al. [3] introduced a robust DL technique, named Faster-RCNN based on ResNet-34, to address the challenge of tomato plant disease detection. The authors innovatively devised a method of annotations to precisely delineate the target areas for analysis. This technique incorporated ResNet-34 within the Faster-Feature RCNN's extractor module, complemented by the inclusion of the Convolutional Block Attention Module (CBAM) to extract intrinsic information. The computed features were then employed to train the Faster-RCNN model, enabling the detection of diseases in tomato plants. Notably, the final accuracy attained by this model reached an impressive 99.97%, underscoring the efficacy of the proposed DL-based technique in achieving highly accurate and precise disease detection in tomato plants.

Geethamani et al. [9] introduced a pioneering method for plant leaf disease identification, employing a deep CNN across 39 diverse classes of plant leaves from various crops. The authors employed a strategic data augmentation approach, encompassing techniques such as image processing, PCA, rotation, scaling, and noise injection. Through meticulous experimentation with different epochs, batch sizes, and dropout rates, the model exhibited robust performance. In a comparative analysis against transfer learning approaches, the proposed model achieved a commendable 96.4% classification accuracy, highlighting its efficacy in advancing plant leaf disease identification methodologies within the realm of agricultural technology.

Juncheng et al. [10] devised a methodology for identifying leaf diseases in cucumber plants through the utilization of a deep convolutional neural network (DCNN). Anthracnose, powdery mildew, and target leaf spots, common afflictions of cucumber plants, were the primary focus of the study. The authors strategically implemented data augmentation techniques to address overfitting concerns and augment the dataset. The DCNN model demonstrated a significant improvement in accuracy, achieving a 93.4% score, surpassing the performance of classic machine learning algorithms like Random Forest and Support Vector Machine (SVM), as well as the AlexNet architecture. This study enhances disease identification in cucumber plants by demonstrating the effectiveness of DCNNs and data augmentation strategies in improving accuracy in the field of agriculture.

Deshpande and Patidar [5] proposed an automated method for detecting plant leaf illness using a DCNN. In order to tackle the problem of data imbalance, the authors included the GAN to do data augmentation. A comprehensive series of experiments was carried out, specifically targeting ten categories of tomato plant illnesses obtained from the database of Plant Village leaf disease. The proposed strategy exhibited exceptional effectiveness, with a precision of 99.74%. The significant enhancement over traditional approaches highlights the potential of DCNNs and GAN-based data augmentation in improving the accuracy of plant leaf disease detection systems, hence contributing to developments in agricultural technology.

Lucas Nachtigall et al. [11] proposed a model based on CNN tailored for the identification of disorders in apple leaf diseases. Leveraging the pre-trained architecture of AlexNet, the authors adeptly classified diseases within a dataset comprising 1450 apple images designated for training. The dataset comprised five classes, delineated into two for malnutrition, one for damage due to herbicides, and two for damage resulting from diseases, each class containing 290 images. The distribution for training, validation, and testing encompassed 192, 83, and 15 images, respectively, for each class. In a comparative analysis against Shallow Neural Network methods, the deep CNN model demonstrated substantial improvement, achieving an impressive accuracy rate of 97.3%. This study underscores the effectiveness of deep CNNs in enhancing the precision of apple leaf disease identification within the realm of agricultural technology.

Sharada Mohanty et al. [12] leveraged the comprehensive Plant Village dataset, encompassing 38 classes of images, including both colored and grayscale variations. The author conducted training and testing utilizing both types of images. The study explored both scratch and transfer learning models, employing pre-trained architectures such as AlexNet and GoogLeNet for the classification of plant leaf diseases. The pinnacle of accuracy, reaching 99.34%, was attained through the transfer learning approach utilizing GoogLeNet on colored images, employing an 80-20 training-test distribution. This research underscores the effectiveness of transfer learning models, particularly GoogLeNet, in achieving high accuracy rates for the plant leaf diseases classification, contributing valuable insights to the field of agricultural technology.

Hari et al. [1] introduced the CNN model named the Plant Disease Detection NN (PDDNN). Utilizing an expanded dataset comprising 14,810 images from various crops, the proposed model featured a 16-layered CNN architecture designed for effective feature extraction. Incorporating essential components such as max-pooling layers and activation functions, the model demonstrated a commendable accuracy rate of 86%. This study underscores the significance of tailored CNN architectures, such as PDDNN, in enhancing accuracy in plant disease detection, contributing valuable insights to the realm of agricultural technology.

Aravind Krishnaswamy Rangarajan et al. [13] showcased proficiency in classifying tomato leaf diseases through the utilization of pre-trained architectures for training a dataset comprising 14,828 images. Employing both AlexNet and GoogLeNet, the authors achieved notable success, attaining an impressive accuracy rate of 99.18%. This study highlights the efficacy of leveraging established pre-trained models for accurate classification of tomato leaf diseases, contributing valuable insights to advancements in plant disease detection within the realm of agricultural technology.

Amara J et al. [14] introduced a DL model for the identification of Banana leaf diseases. The authors employed the Lenet architecture, configuring it as a CNN model. This model was specifically designed to address challenges inherent in the detection of banana leaf diseases, including variations in illumination, size, pose, and real-world image conditions. The utilization of DL techniques, particularly the Lenet architecture, demonstrated the ability to increase the accuracy and robustness of banana leaf disease identification under diverse and challenging environmental factors.

Mahmudul Hassan et al. [4] propose the use of depth-separable convolution that effectively decreases the quantity of parameters and computing costs. The approach implemented in this study, namely InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, were trained on a dataset consisting of different 38 classes for 14 different plant species. These models demonstrated remarkable accuracy rates in classifying diseases, ranging from 97.02% to 99.56%. The deep CNN model outperformed standard approaches in terms of success rate and required less time for training. The practical use of MobileNetV2 is enhanced by its compatibility with mobile devices, making it a potential deep CNN model for efficient and real-time disease identification in agricultural systems.

Alvaro Fuentes et al. [15] analysed tomato plant illnesses using three well-known deep learning architectures: Region-based Fully Convolutional Network (RFCN), Single Shot Multibox Detector (SSD), and Faster Region-based CNN. The authors conducted experiments by incorporating VGG-16 and ResNet (Residual Net) algorithms into each design, aiming to improve the accuracy of disease identification. This paper thoroughly examines the interaction between several deep learning architectures and known methods, offering useful insights into improving accuracy in the detection of tomato plant illnesses.

Lu Y et al. [16] Implemented a neural network that utilises deep convolution layers to automatically detect and classify rice illnesses. Through experiments with a dataset of 500 natural rice photos, the suggested technique achieved a significant accuracy of 95.48%. The dataset comprised of photos depicting diseased leaves exhibiting ten unique types of illnesses, as well as photographs of healthy leaves. The authors utilised a rigorous 10-fold cross-validation technique, enhancing the dependability of their results and emphasising the efficacy of their suggested model in precisely detecting different rice diseases.

Sladojovic et al. [17] developed a model for the classification of plant diseases utilizing images encompassing both healthy and affected leaves, featuring 13 different types of lesions. To mitigate the risk of overfitting in CNN, the dataset underwent augmentation through changes in resolution, size, cropping, and other factors. This meticulous approach to data augmentation contributed to the avoidance of overfitting issues. The model yielded a notable accuracy of 96.03%, demonstrating the effectiveness of the proposed methodology in accurately classifying plant diseases based on visual features.

Saeed Alaa et al. [18] utilised two pre-trained CNNs, namely Inception V3 and Inception ResNet V2, to diagnose tomato leaf disorders. The classification involved distinguishing between healthy and diseased tomato leaf images. The models were trained using a dataset that consisted of photographs from both an open-source database (Plant Village) and images recorded in the field. In total, there were 5225 images in the dataset. The investigation encompassed a range of dropout rates, ranging from 5% to 50%. The findings showed that the Inception V3 model, with a dropout rate of 50%, and the Inception ResNet V2 model, with a dropout rate of 15%, performed the best. These models achieved an accuracy of 99.22% and a loss of 0.03. This paper highlights the efficacy of utilising pre-trained CNNs for precise categorization of tomato leaf diseases, providing valuable information on the ideal dropout rates to enhance model performance.

Intan Nurma Yulita et al. [19] proposed an approach for deep learning that incorporates a DenseNet architectural implementation. The optimisation of this model required the adjustment of many hyperparameters. The authors created an optimum model by utilizing 2 hidden layers, a DenseNet trainable layer on dense block 5, and a dropout rate of 0.4. The assessment of this model using a 10-fold cross-validation procedure demonstrated a noteworthy accuracy rate of 95.7% and an F1-score of 95.4%. In addition, the authors created a smartphone app specifically designed to identify tomato plant leaves, demonstrating the actual use of their proposed deep learning algorithm in real-life situations.

Bin Liu et al. [20] presented a method for identifying leaf diseases in grape leaves. The author employed a generative adversarial network (GAN) to augment the dataset, enhancing its diversity and size. The augmented dataset was then utilized for training and testing with a pre-trained architecture. The proposed method demonstrated significant success, achieving the highest cusses rate of 98.70%. This approach highlights the effectiveness of using GANs for data augmentation in improving the accuracy of leaf disease identification models for grape leaves.

Guerrero-Ibanez et al. [21] presented an innovative CNN model to detect and categorise diseases affecting tomato leaves. The model was trained using a dataset that is accessible to the public. In order to address the issue of overfitting in the training data, Generative Adversarial Networks were utilised to produce samples that possess comparable features. The results indicated that the suggested model showed exceptional performance in identifying and categorising illnesses in tomato leaves, with a validation dataset accuracy of 99.64%. This study highlights the efficacy of employing convolutional neural networks and generative adversarial networks for reliable and precise detection of tomato leaf diseases.

III. COMPARATIVE ANALYSIS

In this section, a comparison has been made between different methodologies used by different authors exclusively in 2023 as mentioned in tabular form in table 1.

References	Dataset	Feature Selection Techniques	Results
Guerrero-Ibanez et al. **[21]**	Tomato Leaf Disease Public Dataset	CNN	Accuracy: 99%
Saeed Alaa et al. **[18]**	Village Dataset for Tomato Disease.	Inception V3, Inception ResNet V2	Accuracy: 99.22%
Intan Nurma Yulita et al. **[19]**	Tomato Plant Leaves Image Dataset	DenseNet	Accuracy: 95.7%
Deshpande et al. **[5]**	Plant Village Leaf Disease Dataset	Deep CNN	Accuracy: 99.74%
Roy et al. **[2]**	Plant Village Leaf Disease Dataset	PCA with Deep NN, F-R CNN	Accuracy: 99.60%
Binnar et al. **[6]**	Private Dataset	AlexNet, MobileNet, Inception-V3	Accuracy: 97.52%

Table 1. A Tabular Representation of the Methodologies Proposed by Different Authors after 2023 published papers

V. Conclusion

In this study comprehensive examination of machine and deep learning techniques for plant disease recognition and classification reveals their pivotal role in advancing agricultural practices. The integration of these techniques, particularly deep learning, exhibits remarkable strides in automating disease detection across various crops. The study underscores the potential of advanced computational methods to aid farmers in achieving automatic and precise identification of a spectrum of crop diseases. The extensive research delves into diverse machine and deep learning approaches, shedding light on their respective contributions to plant disease detection. Notably, the comparative study between machine and deep learning techniques unveils the superior efficacy of deep learning, particularly in recent years, marking a substantial leap in the identification of plant leaf diseases. The summarized techniques and mappings for recognizing disease symptoms emerge as valuable resources for scientists engaged in plant disease detection. Despite the significant progress observed, our analysis discerns notable research gaps that warrant attention. Addressing these gaps will be instrumental in implementing effective techniques for plant disease detection. As technology evolves, we anticipate that this work will serve as a foundational tool, guiding scientists and practitioners toward more refined and efficient approaches in the ongoing endeavor to secure global food security through advanced agricultural technologies.

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