International Journal of Medical, Pharmacy and Drug Research (IJMPD)
Article
DOI: https://dx.doi.org/10.22161/ijmpd.7.2.2
Peer-Reviewed Journal
Int. J. Med. Phar. Drug Re., 7(2), 2023
ISSN: 2456-8015

Survey on Plant Disease Detection using Deep Learning based Frameworks

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Received: 03 Feb 2023; Received in revised form: 04 Mar 2023; Accepted: 20 Mar 2023; Available online: 30 Mar 2023
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Abstract— *Early identification of plant diseases is crucial as they can hinder the growth of their respective species. Although many machine learning models have been utilised for detecting and classifying plant diseases. The advent of deep Learning, a subset of machine learning, has revolutionised this field by offering greater accuracy. Therefore, deep learning has the potential to greatly enhance the accuracy of plant disease detection and classification. Recent research progress on the use of deep learning technology in the identification of crop leaf diseases is reviewed in this article. The current trends and challenges in plant leaf disease detection using advanced imaging techniques and deep learning are presented. This survey aims to provide a valuable resource for the researchers investigating the detection of plant diseases and detection of those using state of the art models for ease of saving time and cost. Additionally, the article also addresses some of the current challenges and issues in the detection process that need to be resolved.*
Keywords— ***Plant Disease Detection, Deep Learning, Survey, Convolutional Neural Network, Agriculture.***

I. INTRODUCTION

Plants are the producers and the most important part in the food chain after the sun. Plant health is an important consideration for the environment as well as for the food safety and food security of the world population. In fact it is closely linked to the "one health" concept [1], which addresses the ways of fighting the health issues of humans and animals and environmental issues and controlling the spread of diseases [2]. Considering the importance of plant health the United Nations declared the year 2020 as the International Year of Plant Health [3]. In their findings, Serge Savary et. al. estimated the loss of yield due to plant disease for five major crops viz. wheat, rice, maze, potato and soybean ranges from 8.1% to 41.1% [4]. If the global economy is considered then plant diseases cost over 220 billion dollars per annum [5]. Thus disease control and mitigation is of utmost importance. To do so, it is necessary to understand and classify diseases properly.

Plants with a disease typically have noticeable stains or lesions on their leaves, shoots, fruits or flowers. The majority of diseases and pest conditions exhibit a distinct visual pattern that can be utilised to specifically identify irregularities. Most disease signs may first develop on the leaves of plants, which are typically the main source for identifying plant illnesses [6]. Here is an example of some images in Fig. 1 from various datasets [7], [8], [9], [10] showing various plant diseases.

On-site identification of diseases of plants is typically done by agricultural experts, or by farmers using their own knowledge. This approach is not only arbitrary, but also arduous, time-consuming, and ineffective. Inexperienced farmers are more likely to make mistakes and utilise medications carelessly when making identifications. Environmental contamination brought on by quality and output will result in avoidable financial losses. In order to overcome these difficulties, the application of techniques for image processing for identifying plant diseases has emerged as a popular study area.

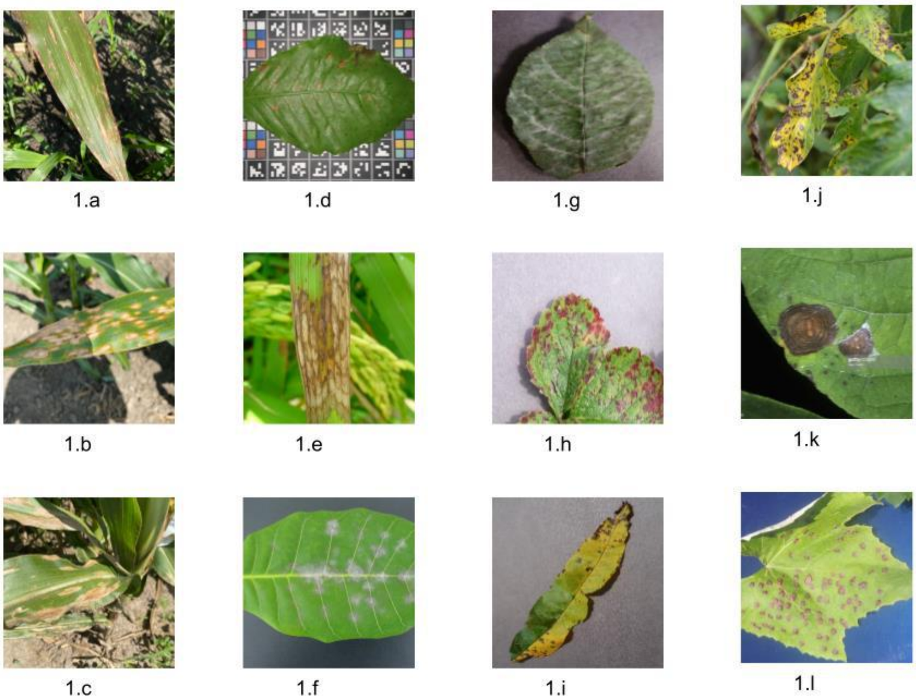

Fig. 1: Some images from various datasets of various plant diseases. From [10] 1.a: Grey Leaf Spot, 1.b: Northern Leaf Spot, 1.c: Northern Leaf Blight. From [9] 1.d: Coffee Blister Spot, 1.e: Rice Leaf Scald, 1.f: Cashew Powdery Mildew. From [7] 1.g: Cherry Powdery Mildew, 1.h: Strawberry Leaf Scorch, 1.i: Peach Bacterial Spot. From [8] 1.j: Tomato Septoria Leaf Spot, 1.k: Potato Early Blight, 1.l: Grape Leaf Black Rot.

While using tiny data sets and creating theoretical conclusions, traditional image processing algorithms produced acceptable results and performance for plant disease identification using leaf pictures. Deep learning is being vividly used for script identification [30-38] and also for human disease detection [39-44]. Deep learning has revolutionised the field of computer vision, specifically in the field of object detection and image classification. Deep learning along with transfer learning is now regarded as a promising tool to enhance the ability of plant disease detection systems in order to achieve better results, widen the scope of disease detection, and implement a useful real-time system for identification of plant diseases.

There are plenty of reviews and survey articles available [45-53] but this article surveys the most recent advancement in the field of plant disease detection using various deep learning techniques. To track this recent advancement, articles that are openly accessible and published in 2022 and 2023 have been selected as references.

This paper contains a total of 5 sections. Section 2 introduces the various datasets used by the articles which are under the survey. The section 3 presents the surveys of 15 selected articles on recent advancement of plant disease detection. The next section discusses the future scope available on the topic. The last section provides a conclusion.

II. DATASET

Typically, for deep learning dataset comprises three subsets: the training set, validation set, and test set. The training set facilitates the learning process of the model, while the validation set is commonly utilised to fine-tune hyperparameters during the training phase. On the other hand, the test set contains data samples that the model has not previously encountered, and it serves as a means to assess the performance of the deep learning model. In this section, the available datasets and how they have been developed i.e., the source of the images are discussed.

Khan et al. [11] used a dataset [12]. Six distinct diseases for cucumber leaf, including downy mildew, powdery mildew, mosaic, anthracnose, angular spot, and blight, are included in this dataset. Initially, each class comprises 100 to 150 photos, along with them they created a straightforward method for data augmentation that consists of four operations: vertical and horizontal flip, rotation of 45 and 60 degrees. The number of photos in each class is increased to 2000 by using this approach, which is applied to each class of cucumber illness. This enhanced dataset is used to train deep models in subsequent rounds.

A well known dataset called "PlantVillage" which was originally published as [14] but later republished in a paper and available as [7]. This dataset contains a total of 54303 images that includes images of 14 different plants and 38 different diseases. Here is some example shown in Fig. 2 collected from a dataset. The article [13] used 2152 images of 3 classes of potato leaves taken from [14] and 1700 images self collected of two potato leaf disorders. This dataset is also used as a part or as a whole in the articles [15], [16], [17], [18], [58], [59].

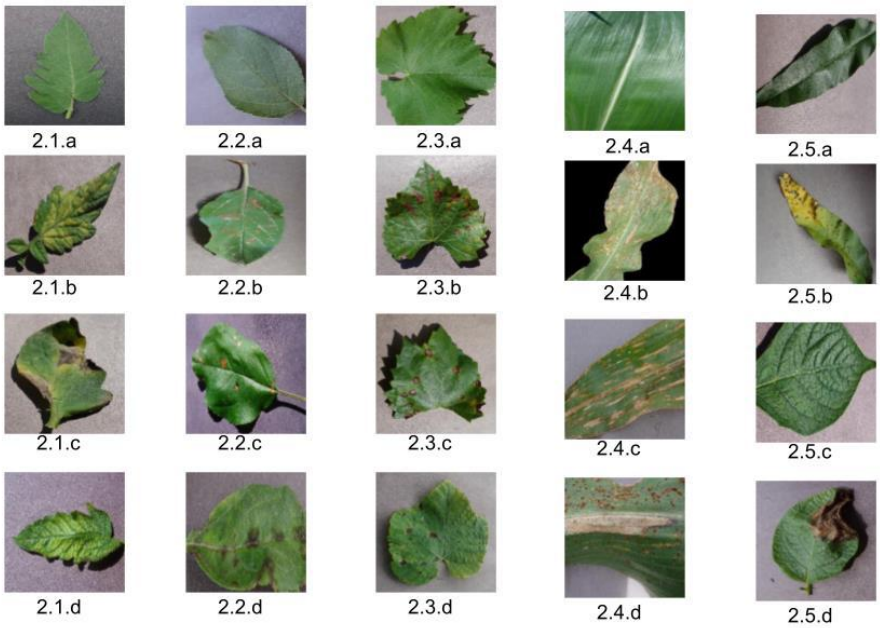

Fig. 2: Some example images of - 2.1.a: Healthy tomato leaf, 2.1.b: Tomato leaf with Leaf Mold, 2.1.c: Tomato leaf with Early Blight, 2.1.d: Tomato leaf with Mosaic virus, 2.2.a: Healthy apple leaf, 2.2.b: Apple leaf with Cedar Apple Rust, 2.2.c: Apple leaf with Black Rot, 2.2.d: Apple leaf with Apple Scab, 2.3.a: Healthy grape leaf, 2.3.b: Grape leaf with Esca (Black Measles), 2.3.c: Grape leaf with Black Rot, 2.3.d: Grape leaf with Leaf Blight, 2.4.a: Healthy corn leaf, 2.4.b: Corn leaf with Common Rust, 2.4.c: Corn leaf with Gray Leaf Spot, 2.4.d: Corn Leaf with Northern Leaf Blight, 2.5.a: Health Peach Leaf, 2.5.b: Peach leaf with Bacterial spot, 2.5.c: Healthy potato leaf, 2.5.d: Potato leaf with Late Blight.

Along with [7], the article [15] used datasets [19], [20], [21], [22] to create a dataset consisting 58 plant disease classes and one no-leaf class. [23] used a custom made dataset [24] having three classes of corn diseases. A guava leaf dataset [26] of four disease classes is used by [25]. In the article [27] about wheat diseases, the authors used their own dataset of 19160 images in five different classes, a small part of which is available at [28].

Along with the dataset PlantVillage dataset [14], the article [16] used Plantdoc dataset [8], Digipathos dataset [9], NLB dataset [29] and CD&S dataset [10]. CD&S dataset is a custom dataset of images acquired from the Purdue Agronomy Center for Research and Education (ACRE) consisting of three classes of diseases: Northern Leaf Blight, Northern Leaf Spot and Gray Leaf Spot.

Algani et al. [54] used a dataset for citrus fruits and leaves [60]. Yong et al. [55] used another dataset [61] of oil palm seedlings for their work. Ma et al. [56] created their own dataset collecting images from Jilin Academy of Agricultural Sciences. Guerrero-Ibañez and Reyes-Muñoz [57] used a public dataset [62] of tomato leaves with 11000 images of 10 categories. They have also added 2500 images of their own collection.

The consolidated summary of the available plant disease datasets are tabulated in Table 1.

Table 1: Summary of the state of the art plant disease datasets.

Author(s)	Year	Dataset specification
Zhang et al. [12]	2017	Six classes of cucumber leaf.
Hughes and Salath [14]	2015	38 disease classes of 14 different plants.
J and Gopal [7]	2019	38 disease classes of 14 different plants.
Singh et al. [8]	2020	17 classes of disease of 13 different plants.
Barbedo et al. [9]	2018	171 disease class and 21 different plants.
Ahmed [10]	2021	3 classes of corn disease.
Hu et al. [19]	2019	3 classes of tea leaf disease.
Kour and Arora [20]	2019	2 classes with 16 subclasses of 8 different plants.
Krohling et al. [21]	2019	Healthy and diseased Arabica coffee leaves
Parraga-Alava et al. [22]	2019	Healthy and diseased Robusta coffee leaves
Ahmad et al. [24]	2021	3 classes of corn disease.
Rajbongshi et al. [26]	2022	Images of guava diseases of six classes.
Long et al. [28]	2022	999 wheat disease images with five classes.
Wiesner-Hanks et al. [29]	2018	Images of northern leaf blight of maize.
Rauf et al. [60]	2019	Citrus fruits and leaves dataset.
Azmi et al. [61]	2020	Oil Palm Seedlings images.
B et al. [62]	2020	10 classes of tomato leaves including healthy leaves.

III. STATE-OF-THE-ART METHODS

In this section, recent studies that employ popular machine learning architectures for identifying and classifying leaf diseases are presented. Additionally, some related works are discussed which introduce the modified or improved versions of deep learning architectures to achieve better results.

This study of Khan et al. [11] proposes an Entropy-ELM-based system for deep learning to identify illnesses of cucumber leaves. Pre-trained deep models: VGG16, ResNet50, ResNet101 and DenseNet201 are trained in the suggested framework, and one of them is chosen based on accuracy. This model is then used to select the best features using the suggested Entropy-Elm technique. The feature selection strategy is applied in the step opposite, which involves fusing the characteristics of all pre-trained models. The final stage combines the features from the previous two phases to perform classification. Using a dataset of enhanced cucumber leaves, the proposed framework was tested, and its accuracy was 98.48%. In this article total nine classifiers are used among them there are four types of SVM: Linear, Cubic, Quadratic and MG SVM and five types of KNN: Fine, Weighted, Subspace, Cosine, Cubic and Medium KNN. Each classifier's performance is calculated using a variety of metrics, including F1-Score, precision rate, recall rate, time, and accuracy.

Mahum et al. [13] proposed a model that uses the efficient DenseNet 201 architecture. This contains an extra transition layer than the original DenseNet architecture. This improves the compactness and reduces the computation load. The cross entropy loss function is reweighted by the architecture to address the problem of class imbalance inside the dataset. The limited size of the training and testing images lets the model identify illnesses in potato leaves effectively and efficiently. Due to the use of an additional transition layer and preprocessed images, the system also achieves 97.2% accuracy while being computationally quick.

In the article by Pandian et al. [15] a deep convolutional neural network with 14 layers (14-DCNN) has been proposed. To get a balanced dataset along with various public dataset, image augmentation processes like deep convolutional generative adversarial network, neural style transfer and basic image manipulation were used. The coarse-to-fine searching strategy with random search were used to enhance the proposed DCNN model's training performance and to choose the most appropriate hyperparameter values. The training and validation accuracy of the 14-DCNN model were 99.993% and 99.985%, respectively. Since there are less convolutional and pooling operations in the suggested 14-DCNN than there are in transfer learning approaches, the training time was shorter than that of the transfer learning techniques.

Divyanth et al. [23] used three semantic segmentation models: SegNet, UNet and DeepLabV3+ in two stages. Stage one is used to extract the leaf image from the complex background and stage two is used for detection. They have compared the segmentation models by their performance and found UNet performed better for stage one and DeepLabV3+ model in the stage two. They have also calculated the severity of the disease by calculating the area of the disease lesions with improved results.

Nandi et al. [25] have used five CNN models: VGG-16, GoogleNet, ResNet-18, MobileNet-v2 and Efficient Net. They have applied model quantization techniques on above CNN models and found that GoogleNet achieved the lowest size with 97% accuracy. The EfficientNet model achieved 99% accuracy with reasonably low size after quantization.

Long et al. [27] used RMSProp optimizer while training their model CerealConv which gave a classification accuracy of 97.05%. When compared to trained pathologists on a sample of the bigger dataset's photos, the model produced an accuracy score that was 2% higher.

Algani et al. [54] used CNN with Ant Colony Optimization (ACO-CNN). In their study the ACO-CNN model outperformed the C-GAN, CNN, and SGD models in terms of accuracy, precision, recall, and F1-score. The accuracy rates for C-GAN, CNN, and SGD are 99.6%, 99.97%, and 85%, respectively. The F1 score has attained the greatest rate compared to other models since the accuracy rate in the ACO-CNN model is 99.98%.

Yong et al. [55] worked particularly for the detection of Basal Stem Rot. They presented hyperspectral imaging and a deep learning based approach. The method involves dividing the seedling's top-down view into the regions and analysing spectral changes across leaf positions. Segmented images of the plant were generated to assess the impact of background images on detection accuracy using a Mask Region-based Convolutional Neural Network (RCNN). They trained their system using VGG16 and Mask RCNN and obtained the highest precision of 94.32% using VGG16.

Ma et al. [56] extracted multidimensional features from both spatial and channel perspectives using an attention module that was integrated into the cross-stage partial network backbone. Additionally, they incorporated a spatial pyramid pooling module that utilises dilated convolutions into the network to expand the range of crop-disease-related information collected from images of crops. Their proposed model CCA-YOLO obtained an average precision of 90.15%.

Guerrero-Ibanez and Reyes-Muñoz [57] designed a CNN-based architecture that incorporates GAN (Generative Adversarial Network)-based data augmentation techniques for early identification and classification of diseases in tomato leaves. They achieved a highest accuracy of 99.64% in disease classification.

Saeed et al. [58] discussed the identification of tomato leaf diseases by categorising images of healthy and unhealthy tomato leaves utilising the pre-trained CNNs - Inception V3 and Inception ResNet V2. They trained these models using a public dataset known as PlantVillage and obtained a highest accuracy of 99.22% in the validation.

Joshi and Bhavsar [59] used standard deep learning models to classify nine categories of leaf diseases. They also developed a CNN framework to classify the same. Compared with the standard models they obtained better results in their developed model. They reported the highest classification accuracy of 95%.

Ahmad et al. [16] assessed the effectiveness of five standard deep learning models in identifying plant diseases across diverse environmental conditions. These models were trained using corn disease images of public datasets. They observe that using DenseNet169 yielded the highest generalisation performance for identifying plant diseases, achieving validation accuracy of 81.60%.

A fine-tuning method to the developed CNN models was discussed in [17] to classify tomato leaf disease. Authors performed a hyperparameter optimization using the particle swarm optimization algorithm (PSO). The weights of these architectures are optimised using grid search optimization. They also proposed a triple and quintuple ensemble model and classifies the datasets using a cross-validation approach. Using the ensembles method they reported the highest classification accuracy of 99.60%.

Francis et al. [18] described the application of standard deep learning models in agriculture for automatically generating features and developing a predictive system. The authors emphasised the importance of segmentation of diseased areas, transfer learning, and fine-tuning the model. They initially trained on a dataset of healthy and diseased apple leaves and evaluated the performance of multiple MobileNet models with varying depth and resolution multipliers. They obtained a highest accuracy of 99.7% using the combination of Mobilenet and K means clustering method.

In Table 2 the chronological major improvements in the techniques of plant disease detection and classification is presented.

Table 2: Notable improvement in plant leaf disease detection and classification.

Author(s)	Month & Year	Method	Result	Remarks
Khan et al. [11]	Jan' 2022	Entropy-ELM	98.4%	Entropy-ELM is used for feature selection. Classification done using F-DenseNet201
Mahum et al. [13]	Apr' 2022	Efficient-DenseNet201	97.2%	Reduced the impact of class imbalance by using a reweighted cross-entropy loss function.
Pandian et al. [15]	Jul' 2022	14-DCNN	Classification Accuracy 99.96% and Precision 99.79%	Optimised the value of the hyperparameter
Divyanth et al. [23]	Aug' 2022	SegNet, UNet and DeepLabV3+	For estimating disease severity, R^2 value obtained = 0.96	Disease severity estimation done.
Nandi et al. [25]	Sep' 2022	VGG-16, GoogleNet, ResNet-18, MobileNet-v2 and Efficient Net with model quantization techniques	GoogleNet 97% EfficientNet 99%	Model optimization used.
Long et al. [27]	Nov' 2022	CerealConv with RMSProp optimizer	97.05%	Used masked images to verify the working of the model.

Algani et al. [54]	Dec' 2022	ACO-CNN	99.98%	Obtained better results than C-GAN, CNN and SDG models.
Yong et al. [55]	Dec' 2022	VGG-16 and Mask RCNN	94.32%	Hyperspectral imaging used.
Ma et al. [56]	Jan' 2023	CCA-YOLO	90.15%	Dual-attention module used with the CSPNet backbone network
Guerrero-Ibañez and Reyes-Muñoz [57]	Jan, 2023	CNN with GAN data augmentation	99.64%	GAN based data augmentation techniques used.
Saeed et al. [58]	Jan' 2023	Inception V3 and Inception ResNet V2	99.22%	Transfer learning used.
Joshi and Bhavsar [59]	Jan' 2023	Night-CNN	95%	It is relatively quick.
Ahmad et al. [16]	Jan' 2023	VGG16, ResNet50, InceptionV3, DenseNet169, and Xcep-tion	Average generalised testing accuracy of 81.60%	Generalised performance computed.
Ulutaş and Aslantaş [17]	Feb' 2023	Ensemble CNN	99.60%	Particle swarm optimization algorithm used.
Francis et al. [18]	Feb' 2023	Four variants of MobileNet models with and without K-means algorithm.	99.6% without K-means, 99.7% with K-means	With K-means and without K-means algorithms compared.

IV. FUTURE SCOPE

- In future, features can be improved using the Butterfly metaheuristic algorithm and the EfficientNet deep model can be implemented for plant disease detection. Graph CNN and reinforcement learning can also be applied to get better results.
- Many domains, including human illness detection, activity and gesture recognition in security systems, and other plant disease detection issues, can use the Efficient DenseNet 201 model with certain adjustments to its architecture. With the adjustment of the parameters it might be possible to reduce the number of training images and training time with similar or higher accuracy.
- The use of the 14-DCNN model can be extended to analyse disease severity and disease detection using other parts of a plant.
- By measuring the percentage of impacted regions and recommending necessary corrective actions, DL models can be expanded to anticipate severity.
- High accuracy can be achieved for real field plant images with diverse backgrounds.
- Mobile application based plant disease detection systems can be achieved which can run with low hardware resources and with fast detection abilities.

V. CONCLUSION

This study highlighted and analysed various methodologies based on performance, datasets, plant leaf patterns, and diverse classes of disease. It also analysed the limitations of the state of the art and directed towards the potential improvement. The study's conclusion highlights the significance of incorporating computer vision, machine learning, and deep learning into automated devices such as smart mobiles in modern agriculture. In future research, attention should be given to expanding the disease detection system from laboratory settings to field conditions to maintain high accuracy in identification and prioritising research on novel image processing algorithms to facilitate the segmentation and extraction of leaf lesion features in complicated scenarios.

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