

# Plant Disease Diagnosing Based on Deep Learning Techniques: A Survey and Research Challenges

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**Abstract**—Agriculture crops are highly significant for the sustenance of human life and act as an essential source for national income development worldwide. Plant diseases and pests are considered one of the most imperative factors influencing food production, quality, and minimize losses in production. Farmers are currently facing difficulty in identifying various plant diseases and pests, which are important to prevent plant diseases effectively in a complicated environment. The recent development of deep learning techniques has found use in the diagnosis of plant diseases and pests, providing a robust tool with highly accurate results. In this context, this paper presents a comprehensive review of the literature that aims to identify the state of the art of the use of convolutional neural networks (CNNs) in the process of diagnosing and identification of plant pest and diseases. In addition, it presents some issues that are facing the models performance, and also indicates gaps that should be addressed in the future. In this regard, we review studies with various methods that addressed plant disease detection, dataset characteristics, the crops, and pathogens. Moreover, it discusses the commonly employed five-step methodology for plant disease recognition, involving data acquisition, preprocessing, segmentation, feature extraction, and classification. It discusses various deep learning architecture-based solutions that have a faster convergence rate of plant disease recognition. From this review, it is possible to understand the innovative trends regarding the use of CNN's algorithms in the plant diseases diagnosis and to recognize the gaps that need the attention of the research community.

**Index Terms**—Deep learning, Plant disease diagnosis, Plant disease detection, Plant disease recognition.

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## I. INTRODUCTION

Plants are a crucial part of life on Earth as they provide humans with breathable oxygen, food, etc. Furthermore, they provide food for insects and other animals, facilitate weather change, provide clean air, balance the ecosystem, and regulate flooding. In most countries, agriculture crops have become the chief source of economic development. Agriculture plant or crop cultivation has quickly developed in terms of quantity and quality of food production. However, a wide range of factors affect agriculture production such as occurrence of pests and diseases on crops, which, in turn, requires increasing food security. Unfortunately, such diseases are not always detected at an early stage (Fina, et al., 2013).

Plants have been reported to have the following organs: leaf, stem, root, fruit, and flower. In agricultural plants, leaves are an important organ of plants for providing information about the amount and nature of gardening crop (Saleem, et al., 2020). Numerous studies have been conducted on plant leaves as a comparative tool for different purposes such as classification and identification. This is because leaves are often the basis for identification and can be easily perceived, as they are usually green and flattened. Plant diseases can be understood as an unusual state that can interrupt usual plant growth (Shruthi, Nagaveni and Raghavendra, 2019). Plant disease prevention and control have been broadly discussed, because plants are susceptible to diseases and are affected by their outer environment. Normally, plant disease diagnoses have a significant role in monitoring farming systems accurately (Sun, Jia and Geng, 2018).

Plant disease identification is an important mechanism for preventing plant diseases in a complicated environment. Farmers often recognize the symptoms of plant diseases using traditional means, for example, by making naked eye observations and referring to the information in books and internet. (Shruthi, Nagaveni and Raghavendra, 2019). Furthermore, traditional methods such as microscope and DNA sequencing-based approaches have been used to

classify and detect various types of diseases. Such methods, however, necessitate experienced experts in farming, and many farmers are not even permitted to use advanced tools, though most of them own a smartphone for capturing images (Amara, Bouaziz and Algergawy, 2017; Lu, et al., 2017).

The agriculture domain has witnessed massive developments with the aid of technology. Image processing and object detection methods have been used for detecting the infected region in the plant. In addition to their simplicity and accuracy, such techniques are fast (Shruthi, Nagaveni and Raghavendra, 2019; Panigrahi, et al., 2020). Hence, advancements in computer and internet technology can help address the problem of automatic plant disease recognition. Such developments are essential in scientific research for classifying and detecting the symptoms of plant diseases automatically using innovative and intelligent techniques (Saleem, et al., 2020; Bashish, Braik and Bani-Ahmad, 2011).

One of the branches of machine learning is deep learning, which is based on a set of algorithms (Benuwa, et al., 2016). Numerous state-of-the-art deep learning architectures have been used for plant disease detection and recognition. Deep learning algorithms have also been modified by some researchers to enhance the recognition performance of the disease in numerous plant types (see Section II). This paper reviews and compares the methodologies and performances of various deep learning models for the task of plant disease recognition and classification. The remainder of this paper is organized as follows: Section II overviews the extant literature on automated plant disease recognition and discusses the state-of-the-art deep learning methods for data acquisition, preprocessing, segmentation, feature extraction, and classification of plant diseases. Section III discusses research challenges in the said domain. Finally, Section IV summarizes and concludes the current work.

## II. LITERATURE REVIEW

Many approaches have been used in agriculture domain for automatic plant disease recognition in various plant parts such as fruit, root, stem, and leaf. A general plant disease detection and classification system using image processing includes five different stages, namely, data acquisition, preprocessing, segmentation, feature extraction, and classification. Fig. 1 depicts this five-step procedure (Panigrahi, et al., 2020).

### A. Data Acquisition

The first step in plant disease classification and detection system is image acquisition. A wide variety of devices such as digital camera and smart phone camera can be used to capture images of healthy and diseased plants.

### B. Data Preprocessing

The preprocessing step in machine learning or deep learning is important for building an efficient dataset to develop generalizability of the model. In deep learning, a huge amount of data must be collected from different sources such as physical devices, tools, software programs such as

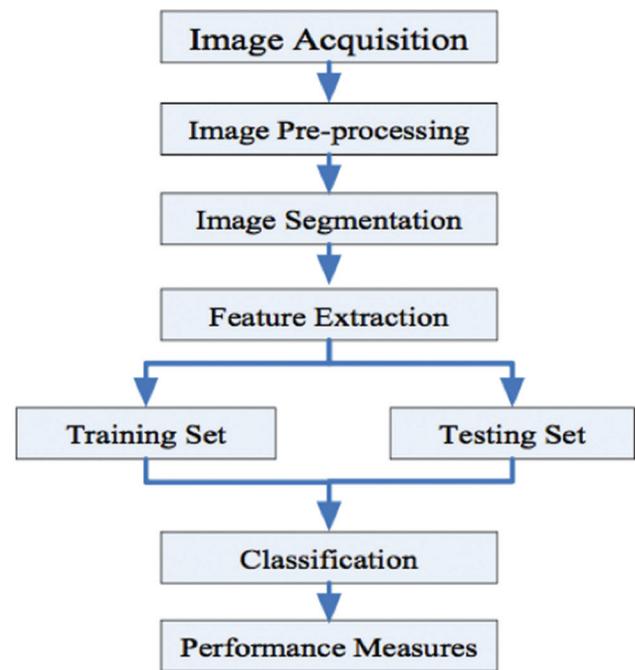


Fig. 1. Flow diagram of the classification process (Panigrahi, et al., 2020).

web crawlers and manual surveys. The model performance may be affected during data collection due to hardware faults, software problems, tool failures, noise, and human errors. Data preprocessing might solve problems such as data not fitting into memory and local storage. It may also help visualize and accelerate the process.

Data preprocessing has an important effect on the performance of a supervised machine learning model. It can solve several kinds of problems on data using transformation, cleaning, normalization, feature extraction, and feature selection before being fed as input to the machine learning or deep learning model (Kotsiantis, Kanellopoulos and Pintelas, 2006). Removing background noise and suppressing undesired distortions have been shown to advance some image features and make the input suitable for further processing (Shruthi, Nagaveni and Raghavendra, 2019; Oo and Htun, 2018). For instance, to boost the reliability of their model, Sladojevic, et al. preprocessed input images by cropping them manually, thereby highlighting region of interest by creating the square around the leaves (Sladojevic, et al., 2016).

In another study, Lu, et al. resized an image from  $5760 \times 3840$  into  $512 \times 512$  RGB image to reduce the running time and dimension of training data (Lu, et al., 2017). In another work, Ashqar, Abu-Nasser and Abu-Naser, 2019 preprocessed input images by resizing them to  $128 \times 128$  pixels, normalizing the pixel values to a  $[0,1]$  range, and balancing dissimilar classes (Ashqar, Abu-Nasser and Abu-Naser, 2019). In (Chen, et al., 2020), Photoshop tools have been used to equally process images into RGB model for computations, and then, these images are resized to  $224 \times 224$  pixels. Table I shows different studies following various approaches for image preprocessing.

TABLE I  
INVESTIGATION OF PRE-PROCESSING TECHNIQUES APPLIED IN PLANT IDENTIFICATION

Authors	Pre-processing methods/Purposes
Amara, Bouaziz and Algergawy, 2017	Image were resized and converted into grayscale
Lu, et al., 2017	Images were resized to smaller size to reduce a running time and dimensions
Sladojevic, et al., 2016	Cropping all images manually and draw a square around the region of interest leaves
Ashqar, Abu-Nasser and Abu-Naser, 2019	Resizee, normalized, and balance dissimilar class of image
Chen, et al., 2020	Photoshop tool used to equally processed images and resized images
Nagasubramanian, et al., 2019	RGB images transformed to HSV color spaces

### C. Data Segmentation

Computer vision and pattern recognition tasks require intelligent segmentation to recognize the content of an image and to facilitate image analysis. Image segmentation process divides the visual input into slices, which are denoted as entities or parts of entities and involve a set of pixels. Segmentation analyzes image data to identify boundaries in images, simplify the illustration of image, and extract meaningful information for further processing. It has a significant role in recognition and categorization of various plant diseases. Deep learning models can be usually applied directly on images to eliminate the process of segmentation.

Several studies have been conducted on automatic segmentation using various techniques. For example, Barbedo realized that image segmentation might be beneficial to separate the region, where the symptoms are located. The accuracy obtained by a convolutional neural network (CNN) trained with localized symptom lesion regions (87%) was found to be higher than original image (76%) (Barbedo, 2018). Moreover, a threshold metric of segmentation can be employed for RGB wavebands of the charcoal rot stem hyperspectral image (Nagasubramanian, et al., 2019). The authors of (Arnal Barbedo, 2019) segmented images into separate spots and lesions, which increased image number and data diversity as well as made it feasible to recognize numerous diseases in the same leaf, where single symptoms were being considered. About 12% accuracy was achieved, which is greater than the case when raw images were used. The authors of (Mohanty, Hughes and Salathé, 2016) segmented leaves to remove unnecessary background information. They opted a method based on a set of masks made by studying the color, saturation constituents, and lightness of a series of image parts. They showed that segmented images perform better than grayscale images but worse than colored images. Table II summarizes various segmentation processes.

### D. Feature Extraction

In pattern recognition, image features play a significant role and are part of an object in image to identify it. Features, most generally, describe image properties such as corners, edges, regions of interest points, and ridges. In plant disease

TABLE II  
SUMMARIZES VARIOUS SEGMENTATION PROCESS AND ADVANTAGES

Authors	Segmentation process	Advantages
Nagasubramanian, et al., 2019	A threshold metrics of segmentation used for RGB wavebands	Employed for RGB wavebands of the charcoal rot stem hyperspectral image
Barbedo, 2018	Symptom segmentation used to separate the region of the symptoms are located	The accuracy obtained with localized symptom lesion regions higher than original image
Arnal Barbedo, 2019	Separate spots and lesions were segmented in the images	Image number and data diversity increases and recognizing a numerous diseases in the same leaf is feasible
Mohanty, Hughes and Salathé, 2016	All extra background information are removed from leaves based on a set of masks that made by study of the color, saturation constituents, and lightness	It has better performance than using images of a gray-scale, and less than colored images

recognition, color, shape, and texture have been used as characteristic descriptors to discriminate between plant object (foreground), and other unrelated objects (background). Image texture feature defines how the patterns of color are dispersed in an image. Image color feature is used to discriminate one disease from another. Moreover, due to diseases that have different shape features which are area, axis, and angle, they used to discriminate diseases (Panigrahi, et al., 2020).

Usually, machine learning datasets include a very huge or high dimensional data, which might contain correlated features, which can be misleading or redundant, which increases space size and makes data processing complex. Dimensionality reduction is a technique that can reduce the dimension of a set of features. Applying dimensionality reduction can represent data using a decreased group of features (Dara and Tumma, 2018; Karthikayani and Arunachalam, 2020).

Whereas traditional pattern recognition approaches adopt handcrafted features, deep learning automatically adapts features in a better and modernized way from a huge dataset (Karthikayani and Arunachalam, 2020). Fig. 2 illustrates a simple way to compare traditional and deep learning methods. The latter is categorized as a group of machine learning algorithms, wherein input layers are basically mapped onto output layers (Mohanty, Hughes and Salathé, 2016). Such methods involve various layers of non-linear processing units for extracting and adapting features. All sequential layers use the previous layer's output as an input (Benuwa, et al., 2016).

In a CNN, dimensionality reduction and the classification process are combined in the same model. CNNs use multiple feature extraction stages and avoid the complicated feature extraction procedure, and to learn the task specific features more efficiently.

Dimensionality reduction techniques can be broadly categorized into two types, namely, feature extraction and feature election (Karthikayani and Arunachalam, 2020), such as shown in Fig. 3 (Uddin, Mamun and Hossain, 2020). In machine learning, feature extraction is an important technique

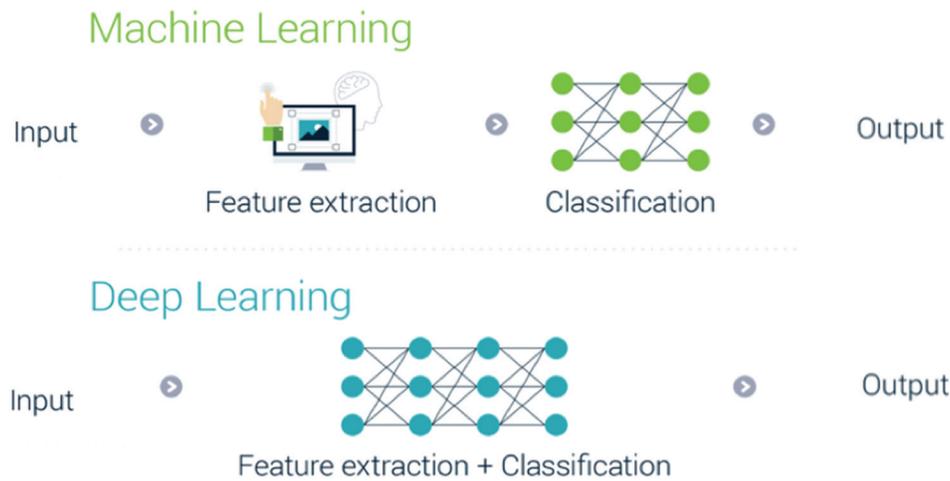


Fig. 2. Feature extraction between a traditional machine and deep learning.

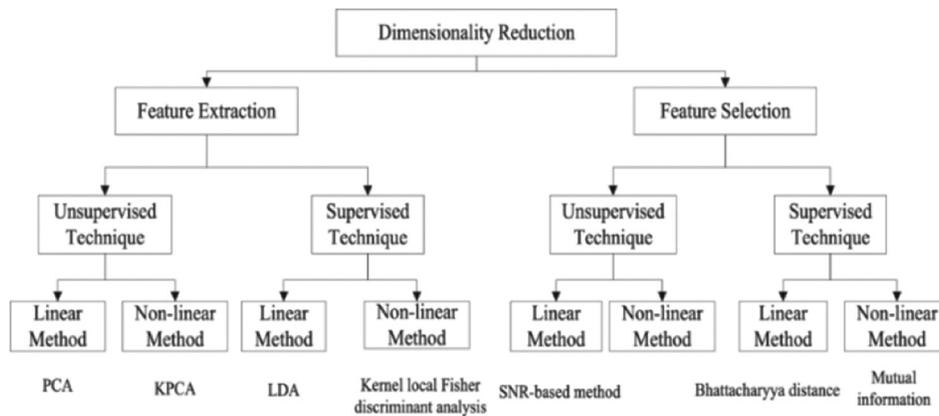


Fig. 3. Dimensionality reduction techniques (Uddin, Mamun and Hossain, 2020).

for converting an input image into a set of features (Dara and Tumma, 2018) and for reducing the dimensionality of feature space (Karthikayani and Arunachalam, 2020). Feature extraction can decrease the number of features needed to define a huge input dataset (Dara and Tumma, 2018) and to delete the data that are less significant (Karthikayani and Arunachalam, 2020). It affects the learning algorithm accuracy for processing the data in a least amount of time (Karthikayani and Arunachalam, 2020).

The second type of technique for dimensionality reduction is feature selection, which aims to find the best features among the whole obtained features. It selects the most important and preferable features among all features from the original dataset. These features can provide relevant information about the data and enable accurate prediction at output stage (Dara and Tumma, 2018; Karthikayani and Arunachalam, 2020).

A CNN is a stack of non-linear transformation functions and can automatically learn representations from the data, to use the numerous feature extraction steps (Khan, et al., 2020; Reyes, Caicedo and Camargo, 2015). It is a specific type of feed-forward neural network (information is fed from layer to layer without reversing) (Zbakh, et al., 2019) and is motivated by biological processes that occur in the visual cortex in the living beings of mind. In the 1980s, CNNs

were initially proposed for digit recognition (LeCun, et al., 1989). Recently, CNN-based deep learning architectures have enabled huge-scale object recognition tasks.

CNNs are capable of extracting features hierarchically and classifying them (Khan, et al., 2020). A CNN has several layers that hierarchically calculate features from images as an input. Deep CNNs have been used for large-scale image classification for the 1<sup>st</sup> time in (Krizhevsky, Sutskever and Hinton, 2017) and exhibited remarkable performance. CNN architecture consists of convolution layers, a pooling layer, an activate function layer, dropout layers, and a fully connected layer at the end, as shown in Fig. 4.

Convolutional and pooling layers act as feature extractors (Amara, Bouaziz and Algerawy, 2017). The Convolutional layer keeps the outcomes of the convolution of filters or kernels of the preceding layer (Durmus, Gunes and Kirci, 2017). These filters or kernels to be learned contain weights and biases; all filters are restricted spatially but expand with comprehensive depth of input volume (Dara and Tumma, 2018). In addition, convolution layers produce a feature map by extracting features of an input image using a filter or kernel (Ibrahim, Sabri and Isa, 2018). The kernel (window) slides over the entire image step by step. The result is taken from summation over the entire image (Zbakh, et al., 2019). Different feature maps yield from

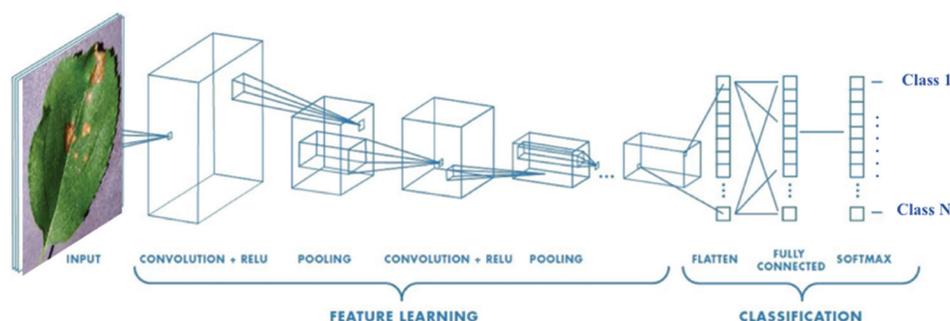


Fig. 4. Convolutional neural network architecture.

multiple convolutional layers and different filters to ensure complete extraction of various features.

The activation function has a significant role in the learning process, and thus, selecting a proper activation function would affect the training dynamics and task performance (Ramachandran, Zoph and Le, 2017). Various activation functions have been used to inculcate non-linear combination of features (e.g., ReLU, sigmoid, tanh, and maxout) (Khan, et al., 2020) and to increase non-linearity of the network (Durmus, Gunes and Kirci, 2017). The most commonly used function is ReLU, which is a piecewise linear function, in which all negative pixel values are replaced by zero, whereas positive pixel values are retained (FatihahSahidan, et al., 2019; Gu, et al., 2018).

The pooling layer works independently over the entire input depth to rescale it. Hence, the feature matrix is decreased (Dara and Tumma, 2018). Pooling layer has a significant concept after activation function to obtain a strong feature versus noise and distortion (Saufi, et al., 2018). It is used to decrease the connection numbers between convolutional layers, reduce the sampling size, and decrease the dimensionality of feature mapping (Ibrahim, Sabri and Isa, 2018; Gu, et al., 2018), reduce neuron size, and reduce overfitting (Durmus, Gunes and Kirci, 2017). Commonly used pooling methods include max, average, mixed, and stochastic pooling. Dropout layers are used to avoid overfitting, which randomly shuts down the neurons in the network (Durmus, Gunes and Kirci, 2017).

#### E. Classification

Classification is generally accomplished using fully connected layer with an activation function softmax, in which computer program uses learned features from input data to categorize the same into predefined classes (Amara et al., 2017) and uses various collections of features (Dara and Tumma, 2018). Many classification techniques have been used in agricultural domain for investigating plant diseases. Traditional machine learning methods have been extensively implemented in agricultural arena. In addition, the deep CNN techniques have been applied for object identification and plant disease categorization and have witnessed tremendous developments in past years. Deep learning has been extensively considered for computer vision tasks in current years, and thus, a huge number of related techniques have been developed. Although it has been proven to be effective

in different classification and detection problems, it is very challenging to grasp unknown objects due to the different shape and posture of objects (Jiang, et al., 2021). For example, LeNet model as a CNN has been used in (Amara, Bouaziz and Algergawy, 2017) to classify two banana leaf diseases, namely, banana speckle and sigatoka. The authors of (Liu, et al., 2017) designed a novel deep CNN architecture for accurately classifying four different types of apple diseases such as mosaic, rust, brown spot, and Alternaria leaf spot. They used a dataset of 13,689 images of unhealthy apple leaves and obtained overall accuracy of 97.62%. Lu, et al. developed an innovative CNN-based identification method to categorize ten common rice diseases. Using this model, they attained an accuracy of 95.48% on a dataset including 500 images of unhealthy and healthy rice leaves and stems (Lu, et al., 2017). The authors of (Ashqar, Abu-Nasser and Abu-Naser, 2019) selected a CNN (ConvNet-based) approach for classifying plant seedlings with a dataset containing approximately 5000 images belonging to 12 different species.

Transfer learning is the process of reusing a pretrained model for solving a new problem that is different from scratch, which involves learning or training data from basic. For instance, the authors of (Chen, et al., 2020) studied transfer learning of deep CNN to classify diseased leaves. They chose VGGNet and inception models for improving the learning capability of small lesion signs. The authors of (Arnal Barbedo, 2019) used a pretrained CNN that employed GoogLeNet architecture to study the use of separate spot and lesions, instead of using whole leaves and classified various plant infections. They concluded that the accuracy attained from separate lesions and spots was 94%. Mohanty, et al. evaluated and focused on two famous deep CNN models, namely, AlexNet and GoogLeNet, trained using scratch and transfer learning, to classify 14 crop classes and 26 diseases. They noted that GoogLeNet reliably performs better classification based on training transfer learning on images of unhealthy and healthy leaves, and attained an accuracy of 99.35% (Mohanty, Hughes and Salathé, 2016). In addition, Nagasubramanian, et al. improved a technique named a supervised 3D-CNN for learning the spectral and spatial information of hyperspectral images of healthy leaves and charcoal rot disease categorization examples in soybean stems. They explained the significance of specific hyperspectral wavelengths in categorization using a saliency map-based visualization technique and obtained a 95.73% classification

accuracy (Nagasubramanian, et al., 2019). A state-of-the-art CNN model from scratch proposed in (Omer, Ghafoor and Askar, 2022) to diagnosis five cucumber leaf diseases and one healthy leaf. A comparative experiments were conducted based on applying pretrained models (AlexNet, Inception-V3, and ResNet-50) to prove the authenticity of the proposed CNN.

In general, most studies in the extant literature are dedicated to plant disease classification. However, plant disease identification (both localization and classification) is a complicated task. Some deep learning techniques have been developed for the purpose of plant disease detection. Deep learning meta-architectures such as Faster Region-based CNN (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD) have been used as a detector for categorization and localization of plant leaves disease (Saleem, et al., 2020), and they have been used in (Fuentes, et al., 2017) for detecting tomato diseases and pests, with suitable performance.

The authors of (Durmus, Gunes and Kirci, 2017) used AlexNet and SqueezeNet models to detect tomato diseases from leaf images and found that the former performed slightly better than the latter in terms of accuracy. Sladojevic, et al. developed an innovative technique based on deep CNN for detecting plant diseases automatically and classified 13 different kinds of plant diseases from the healthy leaf images using CaffeNet CNN architecture. The authors achieved an average accuracy of 96.3% (Sladojevic, et al., 2016). In addition, Hernández and López proposed a method for detecting plant diseases based on a probabilistic programming using Bayesian deep learning procedures (Hernández and López, 2020). Ferentinos used five CNN models, namely, AlexNet, AlexNetOWTbn, GoogLeNet, Overfeat, and VGG to detect plant illnesses using images of healthy and

unhealthy leaves. They reported VGG to be a successful model with a 99.53% success rate on test dataset containing 17,548 images (Ferentinos, 2018). In another study, Ramcharan, et al. applied transfer learning for training a deep CNN Inception v3 to detect three cassava diseases and two kinds of pest damage (Ramcharan, et al., 2017). Table III, summarized that several algorithms had been carried out for plant leaf disease classification.

*F. Dataset*

In the previous studies, various datasets have been used for plant disease classification and detection tasks. Some of those datasets are PlantVillage dataset, which contains healthy and diseased images of five crops, namely, apple (Liu, et al., 2017), corn, grape, potato, and tomato (FatihahSahidan, et al., 2019; Ramcharan, et al., 2017). In addition, the authors of (Ramcharan, et al., 2017) used cassava disease dataset, whereas the authors of (Saleem, et al., 2020) used ImageNet dataset. The authors of (Amara, Bouaziz and Algergawy, 2017) used a real banana disease dataset, in which they derived from the PlantVillage dataset. Several steps are required for the implementation of deep learning algorithms, as shown in Fig. 5 (Saleem, et al., 2020) that start from data collection to visualization mappings.

We can infer from this section that, even though some deep learning models have been developed for image classification in the application of plant disease diagnosis and detection, this is still a fertile area of research and should result in improvements for better recognition of plant diseases in various situations, such as different lighting conditions and taking real background into consideration. It also concluded that leaf is the most commonly used plant organ for classifying plant diseases, as its image can be easily

TABLE III  
SUMMARIZES VARIOUS STUDIES FOR PLANT DISEASE CLASSIFICATION

Authors	Methods	Dataset	Accuracy
Saleem, et al., 2020	Faster R-CNN, R-FCN with ResNet , and SSD with Inception	PlantVillage	73.07%
Amara, Bouaziz and Algergawy, 2017	LeNet	PlantVillage (2 types of banana leaves diseases)	0.9757
Lu, et al., 2017	CNN	rice diseases (10 common diseases)	95.48%
Sladojevic, et al., 2016	CNN (CaffeNet )	PlantVillage (13 different diseases)	96.3%
Ashqar, Abu-Nasser and Abu-Naser, 2019	CNN (ConvNet)	Plant seedling dataset	99.48%
Chen, et al., 2020	VGGNet and Inception	Rice plant images	92.00%
Nagasubramanian, et al., 2019	Supervised 3D-CNN	4 soybean genotypes were selected from soybean stem samples	95.73%
Barbedo, 2018	CNN ( GoogLeNet)	Freely available dataset contains almost 50,000 images	94%. from separate lesions and spots
Mohanty, Hughes and Salathé, 2016	AlexNet and GoogLeNet	PlantVillage	99.35% from GoogLeNet
Durmus, Gunes and Kirci, 2017	AlexNet and SqueezeNet	PlantVillage (tomato leaves )	0.9565 from AlexNet
Liu, et al., 2017	CNN (Goo- gLeNet)	Apple images ( 4 common types of apple disease )	97.62%
Fuentes, et al., 2017	Faster R-CNN, R-FCN, and SSD with ResNet	PlantVillage (tomato leaves )	88.20% from RFCN with ResNet 50
Ferentinos, 2018	AlexNet, Overfeat, AlexNetOWTbn, GoogLeNet, and VGG	Openly available database contains 87,848 images	99.53% from VGG

SSD: Single Shot Multibox Detector

collected, and it is green and smooth during all four seasons. Another finding is that it presents that the PlantVillage dataset was used in the majority of the studies. It includes a simple background and several photos of various plant spices with their diseases. However, the actual environment needs to be taken into account for a realistic scenario.

### III. RESEARCH CHALLENGES

Nowadays, deep learning models have attained good performance and promising results in various domains, such as image classification and detection, speech recognition, and object detection. Such models are advanced enough to deal with complicated tasks. Different architectural models have been used in deep learning recently to obtain significant performance and efficiency. Despite the developments and improvements that have been applied to deep learning models in various research studies, especially in plant disease classification and detection, numerous significant research gaps and challenges still need to be addressed before implementing different deep learning architectures for plant disease recognition. Research issues and challenges that have been recognized in this paper are hyperparameter tuning, model overfitting, plant organs, unavailability of plant disease dataset, and different plant diseases.

#### A. Hyperparameter Tuning

The state-of-the-art models automatically learn features from images and classify on the basis of these learned features. Traditional machine learning models, on the other hand, manually extract features and tune them, which can be time consuming. Throughout the training and testing of the model, a set of parameters, for learning process, known as hyperparameters, are used. A large set of hyperparameters are used in various deep learning architectures (Hutter, Lücke and Schmidt-Thieme, 2015).

In every dataset, hyperparameter tuning has a significant effect on training the model to obtain a good performance and

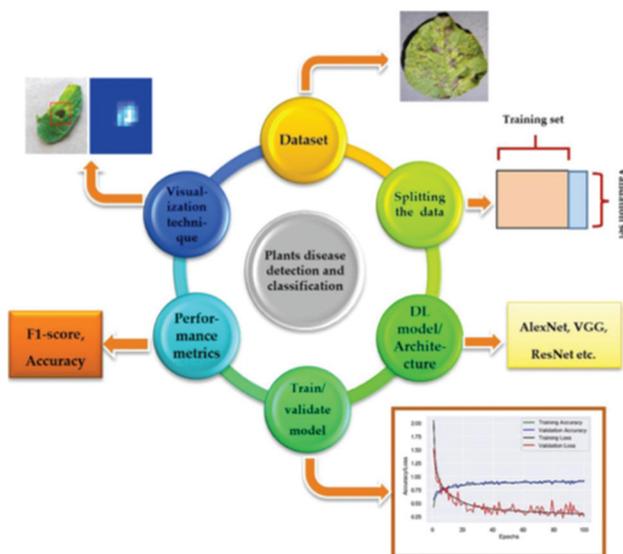


Fig. 5. Flow diagram of deep learning implementation [2].

develops validation errors (Victoria and Maragatham, 2021). Hyperparameters include the parameters of (i) regularization, (ii) network architecture, such as layer numbers and sigmoid transfer function kinds, (iii) sample numbers and learning rates, (iv) preprocessing, such as reducing dimensionality and normalization, and (v) initialization weight parameters. Theoretically, several methods have been treated using hyper-prior and manually using optimization techniques.

Some of these hyperparameters pose a greater challenge of grounded mathematical treatment (Hutter, Lücke and Schmidt-Thieme, 2015). In such instances, hyperparameter tuning of a deep learning architecture is an issue that must be addressed based on empirical data using improving theoretical background and evaluating the performance of the network (Angelov and Sperduti, 2016), such as shown in Fig. 6 (Analytics vidhya, 2020).

For instance, a simplified system or improved technique would require less hyperparameters. On the other hand, a complex system can be customized automatically using hyperparameter optimization algorithms in a given application for optimal performance (Hutter, Lücke and Schmidt-Thieme, 2015). Victoria and Maragatham proposed a Bayesian hyperparameter optimization technique for improving model performance, where all hyperparameter values are optimized (Angelov and Sperduti, 2016).

#### B. Model Overfitting

Overfitting is an issue facing machine learning algorithms, especially deep learning models, in which errors or random noise occur rather than the underlying relationship described in the model (Liu, et al., 2017). Overfitting has been shown to have a negative effect on robust performance of the training set across multiple datasets such as ImageNet, CIFAR-10, CIFAR-100, and SVHN (Rice, Wong and Kolter, 2020), such as shown in Fig. 7. Liu, et al. employed several techniques to avoid overfitting. They used dataset augmentation operations such as mirror symmetry, image rotation, PCA jittering, and brightness adjustment to increase the diversity of training images and enhance the generalizability of their model (Liu, et al., 2017).

The authors of (Rice, Wong and Kolter, 2020) studied data augmentation and regularization techniques to

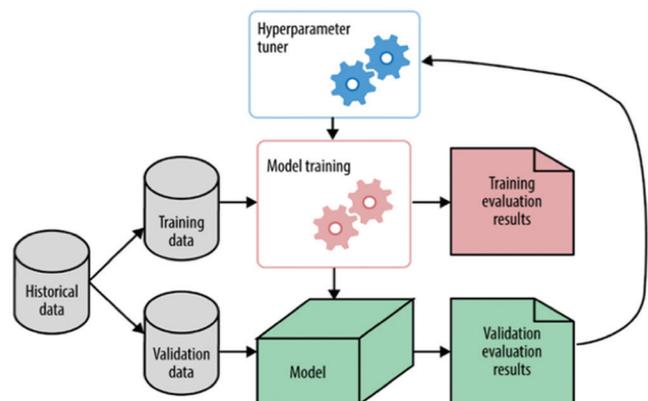


Fig. 6. Hyperparameter tuning process [43].

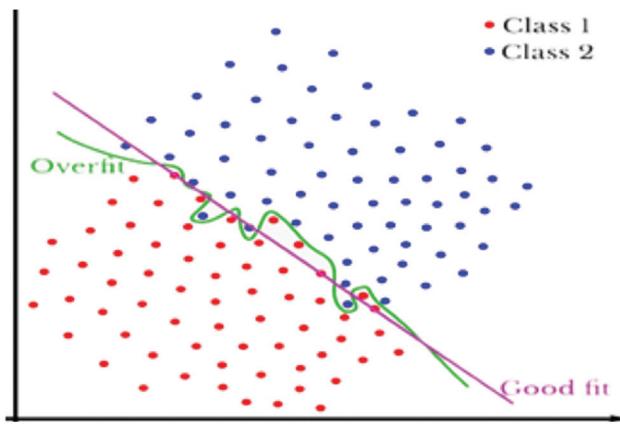


Fig. 7. Overfitting in machine learning.

remedy overfitting. Their experimental testing showed that regularization methods do not robustly prevent overfitting and tend to make the model over-regularized. Furthermore, the authors of (Arsenovic, et al., 2019) used two different augmentation algorithms to prevent overfitting, namely, traditional augmentation methods, like pixel-wise changes or rotations, and training using generative adversarial network. They used local normalization obtained using response-normalization layers and used convolution layers instead of some fully connected layers (Liu, et al., 2017). Furthermore, another way to prevent the model from overfitting using transfer learning is by retraining the last few layers and freezing the first layer (Barbedo, 2018). The authors of (Mohanty, Hughes and Salathé, 2016) changed the data ratio of train and test sets. In addition, two different methods such as training the network model using more examples and changing network complexity like changing structure and parameters of the network have been used to reduce overfitting (Brownlee, 2018). In neural network, dropout means removing units from the network temporarily along with outgoing and incoming connections during training process. Srivastava, et al. used the dropout algorithm for resolving the overfitting problem. They noted that this technique can provide a significant development over regularization algorithms and markedly reduce overfitting (Srivastava, et al., 2014).

### C. Plant Organs

Plants have various organs that have been used as a characteristic to be studied by researchers in various fields, especially in disease recognition and detection task.

Based on this review paper, leaf plant organ had been mostly used by researchers such as in (Saleem, et al., 2020; Amara, Bouaziz and Algergawy, 2017; Ashqar, Abu-Nasser and Abu-Naser, 2019; Nagasubramanian, et al., 2019; Dara and Tumma, 2018; FatihahSahidan, et al., 2019; Ferentinos, 2018; Ramcharan, et al., 2017; Victoria and Maragatham, 2021; and Angelov and Sperduti, 2016), for the purpose of classifying and detecting plant diseases. In (Arnal Barbedo, 2019), instead of using entire leaf, separate spot and lesions have been used.

However, many diseases have been better categorized in other organs using their symptoms. For instance, the stem has

been used in (Lu, et al., 2017; Barbedo, 2018). Furthermore, in Ashqar, Abu-Nasser and Abu-Naser (2019) seeding has been used for classification. Hence, a comprehensive plant image dataset must be constructed to incorporate images of other plant organs and better classify plant diseases.

### D. Challenges Associated with Constructing Large Datasets

In deep learning, a huge dataset with a wide variety is required. However, constructing such a dataset involves challenges. Barbedo realized that plant species, disease variety, variety of conditions in capturing image, and sample numbers in each class of the dataset affect and prevent deep learning models more widely to be used in practice (Barbedo, 2018). Data annotation is one of the important tasks that require expert assistance to label an input image accurately (Kamilaris and Prenafeta-Boldú, 2018).

Researchers have used different datasets in their studies to train deep learning models. For instance, a publicly available PlantVillage dataset is mostly used to calculate the accuracy and performance, which contains many different healthy and diseased images with simple plain background. Yet, most researchers have used similar architectural design and obtained a quite redundant result from their experiments on the dataset such as (Amara, Bouaziz and Algergawy, 2017; Dara and Tumma, 2018; Victoria and Maragatham, 2021; Brahimi, Boukhalfa and Moussaoui, 2017; and Cruz, et al., 2017). Although they have used several aspects of the model for training and testing the system for plant disease recognition, they have still not gained enough new information. Thus, new tests should be considered with supplementary interesting datasets (Barbedo, 2018). Some researchers have also constructed a synthetic dataset (Sladojevic, et al., 2016). However, many challenges still needed to be addressed.

In general, in agriculture field, there is not an enough available dataset to researchers. For this purpose, researchers are required to improve and build a new dataset that includes some different plant organs and different leaf diseases.

### E. Challenges of Plant Diseases

Plant disease management and pathology are faced with ever-growing challenges. On the one hand, agricultural productivity has reduced due to depleting natural resources and diminishing arable lands. On the other hand, due to increasing global population, requests for high quality and varied food have increased. In addition, the evolution and epidemics of plant diseases have globally increased due to intensification, resources such as water, fertilizer, and pesticides (He, Zhan and Xie, 2016). Plant diseases and pests are the major reason that lead to substantial economic losses and reduced plant yields. In technological advancements, the theories of plant diseases and pest diagnoses such as detection and classification have been developed from symptoms and signs of the diseases (Balodi, et al., 2017).

In the future, plant disease management plans, such as an accurate plant disease recognition, are important and must be emphasized more for societal development, food security globalization, climate change, and disease prevention. In the field of plant pathology advancements, some new avenues

for specific and sensitive plant diagnosis procedures have been developed that are coupled with molecular biology, bioinformatics, and biotechnology (He, Zhan and Xie, 2016; Balodi, et al., 2017).

#### IV. CONCLUSION

In agriculture farming, plant diseases and pests affect the food loss production if sufficient care is not given. Therefore, an automatic diagnosis plant disease and detection system is essential, as it has many benefits to people in the field of agriculture, pharmaceutical industry, etc. The automated plant disease diagnosis systems combine the expertise of phytopathology experts with the capacity to extract symptomatic features using CNN algorithms to identify and classify plant diseases and pests. This paper is a review and summarized techniques of the deep CNN-based plant disease diagnosis and detection. It also presents some issues and challenges regarding the plant disease classification, detection and dataset characteristics, due to the diversity of problems and the specificities of real-world scenarios that increase the difficulty to semantically catalog the data in representative datasets. In addition, this review investigated some deep learning architectures, this is still a fertile area of research for researchers to address gaps in different agricultural domains by integrating image processing and machine learning, especially CNN-based approaches. Another finding is, deep learning models should be effective for many illumination conditions; therefore, the datasets should include images from a variety of field scenarios in addition to those that depict the real environment. One can conclude from the review, that the CNN models are a widely used in diagnosis and detecting plant disease and pests, for which an accurate and fast model is necessary. In addition, to comprehend the variables influencing the identification of plant disease, such as the classes and quantity of datasets, learning rate, illumination, and similar aspects, a comprehensive study is necessary.

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