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Plant disease diagnosis using image processing techniques – A review on machine and deep learning approaches

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ABSTRACT

Diagnosis and monitoring of plant diseases at early plant growth stages are crucial to minimizing the disease dissemination and it also facilitates effective plant protection measures. Thus, the automatic and real-time system for the diagnosis of plant diseases is very much needed in the current era of agricultural information. Several techniques and/or approaches of image processing have been studied to address the challenges in the diagnosis of plant diseases through acquired images. Of them, conventional machine learning and advanced deep learning (particularly CNN) approaches are nowadays explored considerably and have demonstrated promising and relatively an accurate classification than those of conventional approaches. The present literature review aims to present and discuss the potential applications of these techniques.

Keywords: *Machine learning, Deep learning, Convolutional neural networks, Image processing*

Introduction

Productive and intensive agriculture are always susceptible to the hazards of climate, pests, and diseases and as a consequence of the food security of any nation. Globally, plant diseases causes major economic losses to farmers. Plant disease had caused several famine in the history of mankind. For instance, starvation due to the Irish famine of potato late blight due to *Phytophthora infestans*, losses of valued resources with an elimination of the American chestnut by chestnut blight due to *Cryphonectria parasitica*, great economical loss to the American corn farmers from southern corn leaf blight due to *Cochliobolus maydis*, and anamorph *Bipolaris maydis* (Maloy, 2005). India had also seen several plant disease epidemics, such as Bengal famine of *Helminthosporium* blight of rice, severe wheat shortage in Madhya Pradesh due to wheat rust, and red-rot epidemic in sugarcane in Uttar Pradesh and Bihar (Raychaudhuri *et al.*, 1972). According to Savary *et al.* (2019), pathogens and pests are largely accountable for the yield losses of 10-28% in wheat, 25-41% in rice, 20-41% in maize, 8-21% in potato, and 11-32% in soybean crops. To this, it is rather being crucial to diagnose, forecast, and manage the plant diseases accurately and timely before it causes a severe crop yield loss.

The diagnosis and observing of plant diseases is typically done in the field by an expert (i.e., plant pathologist), and such processes are sometimes laborious and time-consuming. The early diagnosis and forecasting of plant diseases are rather difficult tasks due to constrained plant pathological laboratories and expertise (Singh *et al.,* 2020). For farmers, without technical knowledge, the plant disease diagnosis is a difficult and expensive task since farmers have to consult experts for effective plant protection measures. Thus, an obvious alternative for the diagnosis and continuous monitoring is image-based processing techniques, which shall cover a large area at a low cost and with relatively high temporal resolution. Remote sensing tools such as proximal, airborne, and/or satellite hyperspectral imaging tools are nowadays commonly used to assess agricultural conditions, and these (particularly proximal and/or air-borne hyperspectral imaging) could be utilized for plant disease diagnosis techniques (Barbedo, 2013; Renugambal and Senthilraja, 2015). Prospective of such imaging tools along with their processing approaches for plant disease identification and monitoring have meticulously reviewed by many researchers (Barbedo, 2013, 2016; Golhani *et al.,* 2018; Martinelli *et al.,* 2015; Ngugi *et al.,* 2020; Petrellis, 2018).

Image processing for plant disease diagnosis

Briefly, image processing involves the enhancement of image features of the targetted regions followed by the extraction of useful information related to diseased leaf for further processing. According to Ngugi *et al.* (2020), image processing techniques (IPTs) along with machine learning algorithms could be potentially explored for plant disease detection that dealt with the challenge of precise and early detection of plant diseases. Authors had described several benefits of IPTs: (i) IPTs shall recognize the plant diseases quickly and accurately based on the images of plant leaves, (ii) severity of the plant disease possibly be assessed through determining the size of deformed or discoloured leaf region with respect to the size of whole leaf region, (iii) IPTs shall make it possible for researchers to in vitro examine disease resistance features of newer crop cultivars, (iv) useful information retrieved using IPTs can be circulated quickly and inexpensively to the remotely located farmers, (v) correct and timely diagnosis of plant disease shall result in more economical and judicious application of plant protection products, and (vi) plant disease experts can consult remotely located farmers without visiting their farms, with the usage of IPTs.

General workflow for diagnosis of plant diseases using IPTs includes image acquisition and image pre-processing, followed by segmentation of diseased leaf portions using several mining approaches (Bukka *et al.,* 2020; Ngugi *et al.,* 2020).

(i) Image pre-processing is to eliminate noise and to boost the quality of the input image. For instance, super-resolution imaging techniques can be used for converting multiple low-resolution images into a high-resolution image, morphological operations (e.g., image resizing, filtering, color space conversion, and histogram equalization, etc.) can be used to remove noise, pre-processing required for shadow removal and image correction.

(ii) Image segmentation is subdividing the input image into foreground and background and/or discovering the region of interest by utilizing algorithms or creating clusters of regions through matching up the correlations between neighbouring pixels. For plant disease diagnosis, segmentation is of two folds, the first is to be done to separate the leaf from the background and another to isolate healthy leaf regions from the infected or diseased regions (Ngugi *et al.,* 2020). Image segmentation is usually performed either by conventional methods (e.g., soft threshold, edge-based, region-based, and clustering methods) or soft computing methods (e.g., mathematical logic, neural network, and genetic algorithm). Iqbal *et al.* (2018) have summarized the segmentation-based techniques with their advantages and limitations.

(iii) Feature extraction is required to mine important information from segmented images such as color, texture, morphological information in order to minimize the extent of sources required to facilitate the classification of the dataset. Statistical operations such as local binary patterns, grey level co-occurrence matrix, color co-occurrence matrix, spatial grey level dependence matrix, and model-based approaches are generally used to extract the textural features. As an advanced tool, trained machine learning algorithms are nowadays used with feature vectors to recognize the feature associated with typical plant diseases. Iqbal *et al.* (2018) have summarized several feature-based extraction techniques with their advantages and limitations.

(iv) Image classification normally deals with a given input feature vector having distinct learned classes. Parametric (e.g., simple and multiple regression and functional statistics) and non-parametric approaches e.g., principal component analysis, fuzzy logic, support vector machine, cluster analysis, partial least square, and neural networks have been utilized for plant disease recognization (Golhani *et al*., 2018). In most cases, it is usually done using a support vector machine (SVM) classifier that makes N-dimensional hyperplanes (i.e., optimally partitions the data into different parts). The SVM conveniently evaluates relevant information, and nearly resemble the neural networks. Iqbal *et al.* (2018) have summarized several Classifiers techniques with their advantages and limitations.

Literature review shows that considerable developments have been made in the image processing and machine learning algorithms to diagnose diseased plants (Golhani *et al.,* 2018; Ngugi *et al.,* 2020; Petrellis, 2018; Singh *et al.,* 2021; Sun *et al*., 2018). Along with imaging techniques, Innovative approaches such as machine and deep learning algorithms have been explored for accurate detection and diagnosis of diseased plants. Hence, in this review article, we present the current advances made in the field of machine and/or deep learning techniques for plant disease identification.

Conventional machine learning algorithms for the diagnosis of plant disease

Machine learning, a subdiscipline of artificial intelligence, aims to algorithms that efficient in finding out and/or conforming their structure (e.g., parameters) based upon the observed records (Sajda, 2006). Machine learning is either supervised or unsupervised process. In supervised machine learning, the machine has been trained to utilize a well-categorized and classified image dataset of diseased leaves/plants. The larger the trained dataset, the more accurate is the performance of the machine learning process. Several machine learning approaches, such as artificial neural network (ANN), decision tree, k-mean, k nearest neighbor, and support vector machine (SVM) have been explored for a range of agricultural researches (Mucherino *et al.,* 2009; Rumpf *et al*., 2010). Amongst all, the SVM has been the most investigated for the detection of plant diseases (Araujo and Peixoto, 2019; Bukka *et al.,* 2020; Gurrala *et al.,* 2019; Sood and Singh, 2020). The literature review relevant to conventional machine learning approaches is summarized in Table 1.

Identification of soybean plant diseases based on color, texture and local characteristics of spots on diseased plant leaves have been studied by Araujo and Peixoto (2019). Authors have used different features extraction techniques (such as color moments technique for color features, local binary patterns for texture features, speeded up robust features, and a bag of visual words algorithms for local features) coupled with SVM classification, with an accuracy of 75.8 % for soybean plant disease identification. Gurrala *et al*. (2019) proposed an image segmentation technique termed modified color processing detection algorithm followed by gray level co-occurrence matrix (GLCM) to extract features from 100 diseased leaves to identify the diseases like anthracnose, leaf spot, leaf blight, and scab. The author has used SVM to classify these diseases, and the results show that the proposed segmentation approach was more efficient and accurate compared to k-mean clustering segmentation.

Es-saady *et al.* (2016) have suggested an approach for automatic recognition of plant diseases, based upon the serial combination approach that composed of two SVM classifiers. Authors tested this algorithm for six plant diseases comprising three types of pest insect damages (leaf miners, thrips, and tomato leaf miner) and three forms of pathogenic disease symptoms (early blight, late blight, and powdery mildew). They utilized three methods (color moment method, GLCM, Otsu method) for feature extraction and obtained ~87% of accuracy for disease detection. Similarly, Prakash *et al.* (2017) and Bhimte and Thool (2018) obtained over 90% accuracy respectively for detection of citrus and cotton leaf diseases using k-mean clustering, GLCM feature extraction, and SVM classifier.

For diagnosis of maize plant diseases, Aravind *et al*. (2018) achieved approximately 83% accuracy using multiclass SVM based on various kernel functions (e.g., linear, polynomial, and radial basis functions) along with speeded up robust features' extraction using histogram and GLCM methods and k-means clustering algorithm. Also, Hlaing and Zaw (2018); Islam *et al.* (2017), and Wahab *et al.* (2019) have utilized a multiclass SVM approach respectively for detecting diseases in tomato, potato, and chili plants, and have achieved 85-95% accuracies. Vamsidhar *et al.* (2019) have considered a novel k-means clustering to obtain the segmentation of the leaf images followed by feature extraction and au-

Table 1. Summary of Conventional machine learning approaches

Crop	Data set	Pre-processing techniques	Segmentation techniques	Feature and Techniques used	Classifier(s)	Accuracy %	References
Soybean	354 Digipathos images	Cutting, rotating, and changing	k-means clustering	Color, texture, local characteristics (LBP), (SURF), (BoVW)	SVM	75.6	Araujo & Peixoto (2019)
Maize	2000 Plant Village images	–	k-means clustering	Textural and Bag of feature (GLCM and Histogram)	Multi-class SVM	83.7	Aravind *et al.* (2018)
Chilli	8 field images	RGBimages to grayscale	k-means clustering	Texture and color features (GLCM)	Multi-class SVM	90.0	Wahab *et al.* (2019)
Citrus family	60 filed images	RGB to L*A*B color space conversion	k-means clustering	Texture (GLCM)	SVM	90.0	Prakash *et al.* (2017)
Potato	300 Plant Village images	–	Thresholds for L*, a* and b* channel	color and texture (GLCM)	Multi-Class SVM	95.0	Islam *et al.* (2017)
Pomegranate	–	Scaling and colour transform	Grab cut segmentation	Edge and colour spaces(Canny edge detection)	–	85.0	Sharath *et al.* (2020)
Cotton	130 field images	image cropping, resizing, color transformation, contrast enhancement and filtering	k-means clustering	color, texture (GLCM)	SVM	98.5	Bhimte & Thool (2018)
Capsicum	70 field images	image resizing, color-space transformation, image enhancement	k-means clustering	texture (GLCM)	KNN, SVMDT, Linear Discriminant	100.0	Sood & Singh (2020)
Tomato	2000 Plant Village images	Median filter RGB to L*A*B colour space conversion thresholdColour negation	RGB threshold Morphological operation	(GLCM and Gray level histogram)	Deep neural network	99.3	Rahman *et al.* (2019)
cucumber	420 Filed, Lab and Scanned Images	Resizing of 128 X128, RGB to L*A*B color	k-means clustering	color and shape	Sparse representation-based classification (SRC)	91.3	Zhang *et al.* (2017)
Tomato	1133 Plant Village, Filed images	Color balance	Histogram of Gradients (HOG), k-means clustering	Shape, texture (PHOG, GLCM)	Random Forest (RF)	93.1	Khan & Narvekar (2020)

Table 1. *Continued ...*

Crop	Data set	Pre-processing techniques	Segmentation techniques	Feature and Techniques used	Classifier(s)	Accuracy %	References
Cereal and Vegetable crop	–	image cropping, resizing, contrast enhancement, filters	hybrid k-means clustering	texture and color features (color co-occurrence method)	Multi-class SVM, Naive Bayes, MLP	95.9	Vamsidhar *et al.* (2019)
Multiple Crops	560 Fields images	Resizing, RGB to HSV conversion, image enhancement	k-means clustering	texture features (GLCM and LBP)	SVM, KNN and Ensemble	98.2	Oo & Htun (2018)
Paddy leaf	–	Resizing, noise reduction, contrast enhancement	k-means clustering	texture features (GLCM)	SVM	95.0	Bukka *et al.* (2020)
Paddy	650 Field images	Resizing, RGB to HSV conversion, Background removal Mask	k-means clustering	colour, texture (mean and standard deviation, GLCM)	Deep Neural Network with Jaya algorithm (DNN_JOA)	94.3	Ramesh & Vydeki (2020)
Grape	137 Filed and downloaded images	Resizing, Thresholding and Gaussian Filtering	k-means clustering	Colour, texture	Linear Support Vector Machine (LSVM)	88.9	Padol & Yadav (2016)
Tomato	3535 Plant Village images	Histogram Matching, The goodness of Fitting (GOF) Test	–	Texture and colour (Scale Invariant Feature Transform (SIFT)	Multi-Class SVM	85.1	Hlaing & Zaw (2018)

thors have found that the multi-class SVM (linear, radial bias function, polynomial kernels) had shown better results in identification and classification of fungal diseases of cereal crops (with ~95% accuracy) whereas neural network was better for the fungal disease of vegetables (with ~85-90% accuracy). With a similar approach of using k-mean clustering and linear SVM technique, various phases of Downey and powdery mildew diseases in grape leaves could be detected with an accuracy of 88% (Padol and Yadav, 2016).

For various bacterial and fungal disease in Capsicum leaves, Sood and Singh (2020) have evaluated tree, linear discriminant, k-nearest neighbor (KNN), and SVM classifiers along with k-mean clustering and GLCM feature extraction method, and results showed that the KNN and SVM had given relatively superior in classifying plant diseases such as anthracnose, bacterial spot, powdery mildew, Cercospora leaf-spot, and gray leaf-spot. Similarly, for identification and classification of plant disease viz., Cercospora leaf spot, bacterial blight, powdery mildew, and rust, Oo and Htun (2018) also found that SVM coupled with GLCM and local binary pattern methods had provided relatively greater detection and classification accuracy of 98 % than those of KNN and Ensemble classifiers.

Contrary, several researchers had obtained relatively greater accuracy for plant disease detection with KNN and/or other classifier algorithms. For instance, Kaur *et al.* (2019) proposed an approach based on region-based segmentation, textural feature analysis, and KNN classifier, which had provided relatively higher accuracy and lower execution time compared to the SVM classifier algorithm for plant disease detection. Devaraj *et al*. (2019) and Khan and Narvekar (2020) have proposed a method involving random forest (RF) for the classification of plant diseases. The proposed method of Khan and Narvekar (2020) attained an accuracy of 93.12% on a combined dataset making use of cross-validation, that reveal that the approach could identify diseases in the existence of a cluttered background. A deep neural network could also be utilized for the detection of plant leaf diseases (Rahman *et al*., 2019; Shima Ramesh *et al*., 2018). Ramesh *et al.* (2018) had classified the paddy leaf diseases employing an optimized deep neural network and Jaya optimization algorithm, and had achieved 98.9% of accuracy for burst affected, 95.78% for bacterial blight, 92% for sheath rot, 94% for brown spot as well as 90.57% for normal leaf image. Similarly, using a deep neural network, Rahman *et al.* (2019) also achieved 99% accuracy in classifying and detecting bacterial spot, late blight, and septorial spot diseases of tomato leaf utilizing the Plant Village database.

Zhang *et al.* (2017) had classified the cucumber diseased leaf images using the sparse representation classification (SRC) classification method. This proposed approach (k-means clustering segmentation, extracting shape and color features, and SRC) was shown to be effective in recognizing seven major cucumber diseases with an overall accuracy of 85.7%, was higher than those of the other methods, i.e., SVM, neural-network, texture feature, and plant leaf image based classifications.

Advanced machine learning algorithms for the diagnosis of plant disease

To address the limitations of conventional machine learning algorithms, deep learning has emerged from cognitive and information theories, and the human neuron learning process along with a strong interconnection structure between neurons is looking to imitate (Nielsen, 2019). The deep learning algorithms depend on best-fit model selection and optimization, and are well-suited to resolve the issues where prior knowledge of features is less desired and labelled data is unavailable for the primary use case (Castrounis, 2019).

Deep learning techniches have been utilized in numerous applications including diagnosis of plant diseases (Gao *et al.,* 2020; Golhani *et al.,* 2018; Jogekar and Tiwari, 2020; Mohanty *et al.,* 2016; Nigam and Jain, 2020; Shruthi *et al.,* 2019), and is believed to be one of the most cutting-edge machine learning and artificial intelligence techniques. Table 2 present an overview of the recent studies that successfully applied advanced deep learning algorithms for the identification of various plant diseases.

Amongst the several potential deep learning algorithms, convolutional neural network (CNN) and deep CNN (DCNN) based models have been extensively used in the field of plant disease identification, and have been demonstrated as robust tools for recognizing plant diseases (Agarwal *et al.,* 2020; Arsenovic *et al*., 2019; Gui and Mbaye, 2019; Ma *et al.,* 2018; Rangarajan and Purushothaman, 2020; Wallelign *et al.,* 2018). According to Wang et al. (2017), deep learning can potentially used for classification of fine-grained disease severity, since the method avoids the labor-intensive feature engineering and threshold-based segmentation. Moreover, an assessment article by Barbedo (2018) extensively discussed the factors that affect the design and effectiveness of deep neural nets applied to plant pathology.

Ma *et al*. (2018) have used a deep convolutional neural network (DCNN) to recognize four cucumber diseases (i.e., anthracnose, downy mildew, powdery mildew, and target leaf spots), and the author achieved over 92% accuracy for both balanced and unbalanced dataset. However, the authors had achieved better with conventional AlexNet classifier due to rich feature presentations.

For recognization and classification of soybean leaf spot disease, Gui and Mbaye (2019) proposed DCNN based on LeNet using an unsupervised fuzzy clustering algorithm for diseased spot segmentation. The proposed DCNN model achieved an accuracy of ~90%, while VGG16 (Visual Geometry Group 16) had achieved ~94% accuracy. Earlier, Wallelign *et al.* (2018) had also achieved a ~99% classification accuracy using a CNN-based LaNet architecture model for the recognization of soybean plant diseases. Recently, Karlekar and Seal (2020) have proposed SoyNet, a CNN based module for soybean plant disease recognition using segmented leaf images, and this model had outperformed the three hand-crafted features based on state-of-the-art methods (viz., SVM, KNN, and probabilistic neural network) and six well-known DCNN based models (viz., VGG19, Google Le Net, Dense121, Xception Net, LeNet, and Res Net 50). Tetila *et al*. (2019) have compared four deep learning models (viz., Inception-v3, Resnet 50, VGG19, and Xception) for recognizing the soybean leaf diseases using unmanned aerial vehicles (UAV) digital negative images. Results shows that deep learning models offered high classification rates with a 99% accuracy. The authors further demonstrated the execution of a deep learning model in a computer vision system under real

Teble 2. Summary of deep learning algorithms approaches

Crop	Dataset	Classifier(s)	Accuracy %	References
Cucumber	1184 Plant Village, Forestry and field Images	DCNN, RF, SVM, AlexNet	DCNN: 93.4	Ma *et al.* (2018)
Tomato	5000 filed images	Faster R-CNN with VGG-16, R-FCN with ResNet-50, SSD with ResNet-50	83.1	Fuentes *et al.* (2017)
Wheat	9,230 images of WDD2017	VGG-FCN-VD16, VGG-FCN-S	95.1-97.9	Lu *et al.* (2017)
Sugar Beet	155 images	Updated Faster R-CNN, Faster R-CNN	95.5	Ozguven and Adem (2019)
Apple	2086 PlantVillage images	Custom CNN	90.4	Wang *et al.* (2017)
Soybean	300 field images (3000 superpixels images)	Inception-v3, Resnet-50, VGG-19 and Xception 99.02	Inception-v3: 99.04 Resnet-50: 99.02 VGG-19: 99.02 Xception: 99.04	Tetila *et al.* (2019)
Tomato	14828 Plant Village images	Alex Net, Goog LeNet	99.2	Mohammed *et al.* (2017)
25 plants	87848 open database images	AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, VGG	VGG: 99.5	Ferentinos (2018)
24 plants	82161 Plant Village images	MobileNet, Modified MobileNet, Reduced MobileNet	AlexNet: 99.5 VGG: 99.53, Modified Mobile Net: 97.6, Reduced Mobile Net: 98.34, Mobile Net: 98.7	Kamal *et al.* (2019)
Corn	50,000 images	GoogLeNet	–	Barbedo (2018)
Maize	500 images (3060 generated images)	Modify Cifar10	98.9	Zhang *et al.* (2018)
Soybean	13243 Plant Village, Forestry Images	VGG, DCNN, SVM	VGG: 93.5 DCNN: 89.8 SVM: 83.2	Gui & Mbaye (2019)
14 different species	54000 images (Plant Village)	SVM and KNN, ResNet 50, Google Net, VGG-16	ResNet 50: 98.0	Mohameth *et al.* (2020)
Apple	2029 field and lab images	INAR-SSD	78.8	Jiang *et al.* (2019)
Soybean	300 and 5000 images	Inception-V3, Resnet-50 and VGG-19	90.2-98.9	Amorim *et al.* (2019)
12 Crops and 42 diseases	18334 Plant Village lab images and 79265 field images	DCGAN, ProGAN and StyleGAN	91.7-93.7	Arsenovic *et al.* (2019)
Soybean	12673 Plant Village images	CNN (LeNet)	99.3	Wallelign et al. (2018)
Soybean	486 PDDB database images	SoyNet	98.1	Karlekar & Seal (2020)
Tomato	17500 PlantVillage images	CNN Model, VGG16, MobileNet and InceptionV3	CNN Model: 91.2	Agarwal *et al.* (2020)
Tomato	13262 Plant Village images	VGG16, AlexNet	96.2	Rangarajan et al. (2018)
14 crops and 26 diseases	PlantVillage images	AlexNet, Google Net	99.4	Mohanty *et al.* (2016)

field conditions, such as diverse lighting conditions, object size, and background effects. Similarly, Amorim *et al.* (2019) also proposed a semi-supervised learning method for soybean leaf using UAV images. Results revealed that deep learning architectures trained with fine-tuning on semi-supervised methods yielded relatively higher classification accuracy of 0.9890 with Inception-V3 in comparison to other state-of-the-art deep learning approaches.

In another study, Agarwal *et al.* (2020) developed a CNN-based model to detect disease in a tomato plant and had obtained relatively greater (91% of average accuracy) than those of pre-trained models such as VGG16, MobileNet, and InceptionV3. However, deep learning meta-architecture (viz., faster region-based CNN, region-based fully CNN, single shot multibox models) combined with VGG net and Residual Network could also perform well for real-time tomato diseases recognition (Fuentes *et al.*, 2017). Rangarajan *et al.* (2018) also tested VGG16 and AlexNet networks for tomato disease classification using the PlantVillage dataset and achieved over 97% accuracy. However, AlexNet provided relatively better accuracy with minimum execution time compared to the deep VGG16 network. The AlexNet and GoogleNet CNN models have also been evaluated by Mohammed *et al*. (2017) for recognition of nine tomato leaf diseases using 14,828 images of tomato leaves (PlantVillage dataset), and of which GoogleNet was found more accurate than AlexNet. Further, the authors used fine-tuning pre-trained models that improve the accuracies of both CNN models.

For automatic detection of leaf spot disease in sugar beet, a modified faster region-based CNN (aster R-CNN) architecture was developed by Ozguven and Adem (2019) using 155 images for model training and testing. The author had obtained an accuracy of ~95% for disease detection and classification. This result shows that the changes in CNN parameters according to the image and regions to be detected could increase the success of faster R-CNN architecture (Ozguven and Adem, 2019).

Lu *et al*. (2017) have presented an in-field automatic diagnosis system for wheat crop disease based on deep learning and multiple instance learning (MIL), and that can be used on mobile handsets to perform real-time diagnosis. Authors had modified two conventional CNN models and developed two architectures, viz., VGG-FCN-S and VGG-FCN-VD16, as a basic model of DMIL-WDDS (deep multiple instances learning-wheat disease diagnosis system) framework. These two architectures achieved mean recognition accuracies of 97.95% and 95.12%, respectively. In the study of Zhang *et al.* (2018), improved GoogleNet and Cifar10 CNN deep learning models were used for recognition of maize plant leaf disease, wherein the number of parameters of the improved models is significantly smaller than that of the VGG and AlexNet structures. Both models can achieve over 98% identification accuracies. Mohanty *et al*. (2016) have used two CNN-based architectures, AlexNet and GoogleNet, for the recognition of 14 crop species and 26 leaf diseases using an open Plant Village dataset. The proposed model had achieved nearly 99% accuracy, manipulating the training-testing distribution set and using various types of training mechanisms and datasets.

Using the apple black rot images in the PlantVillage dataset, Wang *et al.* (2017) evaluated the performance of shallow networks trained from scratch and deep models fine-tuned by transfer learning. The author observed that the deep VGG16 model trained with transfer learning provided an accuracy of 90% on the hold-out test set. It was also reported that recognition accuracy increased with an increase in network depth up to the 8-layers.

For the development of a specialized deep learning model based on specific CNN architecture, Ferentinos (2018) has trained the five CNN models for the identification of plant diseases through simple leaf images of healthy or infected plants. The author had used an open database of over eight thousand, containing 25 different plants in a set of 58 distinct classes of plant or disease combinations, including healthy plants. Of the tested models, a VGG network was the most effecttive model architecture with a success rate of 99%. Similarly, Kamal *et al.* (2019) also evaluated various deep learning modes based on various CNN architectures for classification of plant diseases using simple leaf images. The author proposed a separable CNN model that matched the accuracy of standard CNN with very few parameters, making it an excellent model for embedded devices. With nearly six-times fewer parameters than the VGG, the MobileNet achieved a success rate of 98%. Moreover, Reduce MobileNet (i.e., a pruned version of MobileNet) with the retracted five convolution layers, attained a similar accuracy with greatly reduced parameters (Kamal *et al*., 2019).

Mohameth *et al.* (2020) have utilized deep feature extraction and deep learning technique on the PlantVillage dataset to detected diseased plants. Authors have extracted features using SVM and KNN, followed by transfer learning using fine-tune, and subsequently tested three deep learning models VGG16, Google Net, and ResNet 50. Of the tested models, the ResNet 50 was found the best network to use with an accuracy of 98% compared to VGG16 and Google Net. However, the authors recommend the usage of VGG16 in image classification with a large dataset.

Barbedo (2019) explored deep learning with the use of individual lesions and spots for the task instead of considering the entire leaf region for plant disease identification. The proposed approach increases the variability in the dataset without additional images and also allows the identification of multiple diseases affecting the same leaf.

A modified deep CNN based model, single-shot multibox detector with Inception module and Rainbow concatenation (INAR-SSD), was proposed by Jiang *et al.* (2019) using the GoogleNet Inception structure and Rainbow concatenation for real-time detection of apple leaf diseases, such as Alternaria leaf spot, brown spot, mosaic, grey spot, and rust. The results show that the proposed INAR-SSD model achieved a mean average accuracy of ~79% utilizing the studied dataset, with a high-detection speed.

On the other hand, to address the limitation of the deep learning-based approached, Arsenovic *et al.* (2019) have introduced the use of Generative Adversarial Networks (GANs) to increase the size of the dataset and supplement it. On basis of GAN, the author proposed a novel two-stage architecture called Plant Disease Net, which achieved an accuracy of ~94%. According to the author, efficiency accuracy may be improved by considering additional secondary variables such as location, climate, and plant age.

Conclusion

Applications of various imaging and their pre-processing technologies in plant disease diagnosis are relatively new, and there are many possibilities to be explored these or future cutting-edge techniques for accurate and timely disease identification. This article presents a summary of recent research studies of plant disease recognition using various image processing and machine learning techniques. Of the reviewed studied, the deep learning techniques have outperformed the shallow classifiers trained using hand-crafted features. Deep learning techniques could perform commandingly with the large trained dataset for plant disease recognition. However, the major challenges according to the articles of Ngugi *et al.* (2020) and Barbedo (2018) that needs to further investigated are: (i) limited or unorganized dataset of diseased plants or leaves, hence all-inclusive universal plant disease dataset (having variations due to weather, nutrients, varieties, and other biotic or abiotic stressors) is highly required (ii) conventional image augmentation, that needed to be refined at the microscale, such as symptoms-wise spot/lesion segmentation (iii) current techniques are somewhat unable to discriminate the similar symptoms of multiple plant disorders, thus techniques or approaches is required to distinguish between different plant diseases, plant nutrient deficiencies and insect-pest infections that mostly produces similar stress symptoms, (iv) compact CNN models in embedded, robotic and mobile applications are yet to be examined for a real-time and low-cost monitoring.

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