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Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: a review

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ABSTRACT

A quick and precise crop leaf disease detection is important to increasing agricultural yield in a sustainable manner. We present a comprehensive overview of recent research in the field of crop leaf disease prediction using image processing (IP), machine learning (ML) and deep learning (DL) techniques in this paper. Using these techniques, crop leaf disease prediction made it possible to get notable accuracies. This article presents a survey of research papers that presented the various methodologies, analyzes them in terms of the dataset, number of images, number of classes, algorithms used, convolutional neural networks (CNN) models employed, and overall performance achieved. Then, suggestions are prepared on the most appropriate algorithms to deploy in standard, mobile/embedded systems, drones, robots and unmanned aerial vehicles (UAV). We discussed the performance measures used and listed some of the limitations and future works that requires to be focus on, to extend real time automated crop leaf disease detection system.

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1. INTRODUCTION

India is an agrarian economy, with Arable land accounting for more than 54% of the total land area. India ranks among the world's top producers of rice, wheat, cotton, fruits and vegetables, and dairy products in terms of volume. The demand for agricultural products is growing at an unprecedented rate as our population grows. Good nutrition make sure that human body gets all of the nutrients, vitamins, and minerals it needs to work optimally. Maintaining essential vitamins and minerals is also essential for good health. Preventing and monitoring crop diseases plays crucial role for providing nutrias food. Since they can damage crops, decreasing food supply and chain while also raising food prices. Plant pests and diseases can also reduce the palatability of foods, causing populations to alter their conventional food preferences. In 1970, a disease in soya bean crops, "Sudden Death Syndrome" rapidly increased across the United States (US) and eventually reaching on the whole agricultural areas of the US. So, quick and precise crop leaf disease recognition is dangerous to increasing agricultural yield in a sustainable manner. The motto of Food and Agriculture Organization of United Nations (FAO) is "let be bread".

Crop leaf diseases vary in shape, size, and color. Certain diseases might have the identical color, but dissimilar shapes; while some have dissimilar colors but identical shapes. The model can be developed by capturing the diseased leaves and recognize the patterns about the disease is helpful to get free of crop loss due to disease spread or increase [1]. In this approach, the images are often sent to a core crop leaf disease system for analysis; the system can recognize. The system generates information about the crop leaf disease.

In order to explore the use of Image processing for classifying citrus leaf diseases, a research [2] on 2006, was conducted. For this analysis, four distinct citrus leaf disease groups were used, namely greasy spot, melanose, healthy, and scab. For feature extraction and classification the proposed algorithms based on image-processing techniques were developed. The process of extraction of features used the technique of color co-occurrence, which uses an image's color and texture to achieve specific characteristics that reflect the image. On all data models using intensity features, SAS discriminant analysis, hue and saturation features, hyperspectral image (HSI) features presented the results above 81 percent, and above 95.8 percent respectively.

In 2007 Tellaeche *et al.* [3] proposed two mechanisms: segmentation of images and decision making. To divide cells from the image as low-level parts, image segmentation incorporates simple image processing techniques. 2 area-based attributes computing the relationships between crop rows and weeds define each part. A hybrid supervisory methodology decides, from these properties, whether or not a cell must be sprayed. The decision is depends on the merger of two well-known classifiers (SVM and FM) under the Bayesian system.

To recognize cucumber crop leaf disease based on IP and SVM was introduced in 2008 [1]. To reduce noise from the obtained cucumber disease leaves color images, the vector median filter was initially used. The color picture of the cucumber disease spot on the leaf was derived from the texture, shape and color characteristics. The system used SVM and neural networks classifiers. Shape feature gives more accuracy than the texture and color feature gives faster results. The results showed that SVM performance is better than neural networks. Linear kernel of SVM gives better results than polynomial, radial basic, and sigmoid functions.

In 2014, Gavhale *et al* [4] developed a system that contains four-part image preprocessing model involving (red, green, blue) RGB to different color conversion, image enhancement techniques; segmenting the region of interest (ROI) using K-means clustering for algebraic use to assess the defect and acute areas of crop leaves, extraction and classification of features. Using statistical GLCM and color function by means of mean values, texture feature extraction. Finally, the classification obtained using SVM (polynomial and RBF).

The proposed model in 2015, Mokhtar *et al.* [5] uses the GLCM to detect, whether safe or contaminated, and to classify tomato leaf status. For the classification process, the SVM algorithm with popular kernel functions is used. Datasets of 800 healthy and diseased tomato leaves in total. The N-fold cross-validation technique was used to test the accuracy of the presented method with 99.83 percent accuracy of classification using linear kernel functionality.

Mohanty *et al.* [6] proposed a system in 2016 to recognize plant leaf diseases using DL. They built a deep CNN to classify 14 crop varieties and 26 diseases by a dataset of 54,306 images of PlantVillage dataset. They compared various CNN architectures on transfer learning and scratch training. In the case of the colored version of the dataset, the models work better. The limitation is that the classification of single leaves, facing up, in a homogeneous context, is currently limited.

Rançon e*t al.* [7] compared SIFT encoding and DL feature extractors which are already pre trained, for the recognition of Esca disease in Vineyards. 91 percent overall accuracy was obtained using deep extracted features from the ImageNet database trained MobileNet network, exhibiting the efficacy of transfer learning methods without the need to build a feature extractor of ad-hoc specialized features. The next part was aimed at the identification of diseases (using bounding boxes) inside complete images of the plant. The deep learning core network has been incorporated into a "one-step" detection network (RetinaNet) for this reason, enabling us to execute recognition queries in near real time (approximately 6 frames per second on GPU).

This paper [8] proposes a deep neural network-based real time detection system for pests and diseases of Cole. A bounding box generator first determines to provide bounding boxes of size, location, and class by training the input image with a region-based neural network. Then, for verification, the presenting bounding boxes from each class are fed into the CNN filter bank. The problem of false positives generated by bounding box generators and class inequalities in data sets with incomplete data can be solved by proposed method.

Goncharov *et al.* [9] to provide the solution for the problem of tiny image databases, the deep siamese convolutional network was created. The identification of the 3 diseases namely Esca, Black rot, and Chlorosis disease on grape leaves had an accuracy of over 90%. Panigrahi *et al.* [10] the research focused on traditional machine learning techniques for the recognition of maize crop diseases, such as NB, DT, KNN, SVM, and RF. In order to choose the most apt model with the highest precision for plant disease prediction, the aforementioned classification techniques are analyzed and compared. The RF algorithm provides the best results, with 79.23% accuracy. Sagar *et al.* [11] compared five different architectures: ResNet50,VGG16, InceptionV3, Inception, ResNet, and DenseNet169.They discovered that the best result on the test set was ResNet50 with 94% accuracy, it uses skip connections using a residual layer archive. They computed performance by precision, accuracy, recall and F1 score.

2. RESEARCH METHOD

To detect crop leaf diseases and classification by visual symptoms, there are 5 steps existed in the crop leaf disease detection and classification model architecture: image acquisition, image preprocessing, image segmentation, feature extraction, classification. Table 1 represents various acronyms used in the crop leaf disease detection. Table 2 interprets the model of crop leaf disease detection and classification.

Table 1. Acronyms

Acronym	Abbreviation	Acronym	Abbreviation
ML	Machine learning	KNN	K nearest neighbors
DL	Deep learning	RF	Random forest
IP	Image processing	SURF	Speed up robust features
CNN	Convolutional neural networks	LR	Logistic regression
UAV	Unmanned aerial vehicles	BPNN	Back propagation neural networks
FAO	Food and agriculture organization	ANN	Artificial neural networks
SVM	Support vector machine	R-FCN	Region-based fully convolutional network
FM	Fuzzy K means	R- CNN	Region based convolutional neural networks
GLCM	Gary level co-occurrence matrix	LBP	Local binary patterns
RBF	Radial basis function		
SGD	Stochastic gradient descent		
HSV	Hue, saturation, and value		
HOG	Histogram of an oriented gradient		
SIFT encoding	Scale invariant feature transform		
GPU	Graphical processing unit		
NB	Naïve Bayes		
DT	Decision tree		

Table 2. List of the methods used for the detection of crop leaf diseases

Image acquisition	Image Preprocessing	Image Segmentation	Feature Extraction	Classification
Capturing the images from drones, smart mobiles phones, digital cameras and UAVs	Image augmentation	K-means, Principal component analysis Clustering	Texture, shape and color are the features	Machine Learning
Collecting the images from public datasets	Image resizing, rotations, Flipping, shift, shear, zoom	Thresholding	RGB feature extraction	PNN, SVM, ANN, RBF, KNN, BPNN, NN, DT, RF, NB
PlantVillage	Image Annotations	Color segmentation	color co-occurrence	Deep Learning
Image database of plant disease symptoms (PDDB)	Image Enhancement	Learning based segmentation	GLCM texture extraction	CNN, Optimized CNN
Bugwood image database system	Removing noise	Edge detection	SIFT	LSTM
Wheat Disease Database 2017	Smoothing	Model based segmentation	SURF	Transfer Learning
IPM Images	Histogram equalization	foreground/background	HOG	VGG19, GoogLeNet, AlexNet, ResNet50, Inception_V3, MobileNet
Kaggle	Median filtering	Otsu thresholding		NASNet
UCI repository	Color transformations	Sobel edge detection		SqueezeNet
	contrast Image Enhancement	semantic segmentation		Deep Siamese Neural Networks
	perspective, affine image transformations	contours-based segmentation		Ensemble Models
	Clipping			F-RCNN, SSD, R-FCN

2.1. Image acquisition

This is the first step of crop leaf disease detection and classification. The purpose of this stage is to collect and prepare images dataset that will be used in the further process. This is done by capturing the images from mobile phone cameras, digital cameras, drones and UAV either on real time (site) or in controlled conditions.

2.2. Image preprocessing

Image preprocessing is very important to obtain the better results. To remove the noise color transformations were used. To reduce the size of the image acquired by digital cameras resizing techniques were used. It also helps to reduce memory size. The frequently used image preprocessing techniques in this literature includes cropping the leaves from the acquired images, color transformations, rescaling, background removal, image enhancement, flipping, rotating, Shear, and image smoothing.

2.3. Image segmentation

Image segmentation plays an essential role in crop leaf disease detection and classification. It splits the image into various parts or zones. It explores the image data to extract helpful information for feature extraction. Image segmentation can be done in 2 ways, one is based on similarities and the other one is based on discontinuities.

2.4. Feature extraction

Extracting the features of the substances of an image is called as feature extraction. The most common features found in plant disease detection and classifications are shape, color, and texture. The crop diseases may differ in appearances of the image due to multiple classes. The crop leaf disease system can easily recognize the diseases from the shape of the crop leaf image. The second feature is color is an important. It distinguishes the crop leaf diseases from each other. The last feature, texture portrays the various patterns of the color are spotted in the crop leaf images. The common texture features are energy, entropy, contrast, correlation, sum of squares, sum entropy, cluster shade, cluster prominence, homogeneity.

2.5. Classification

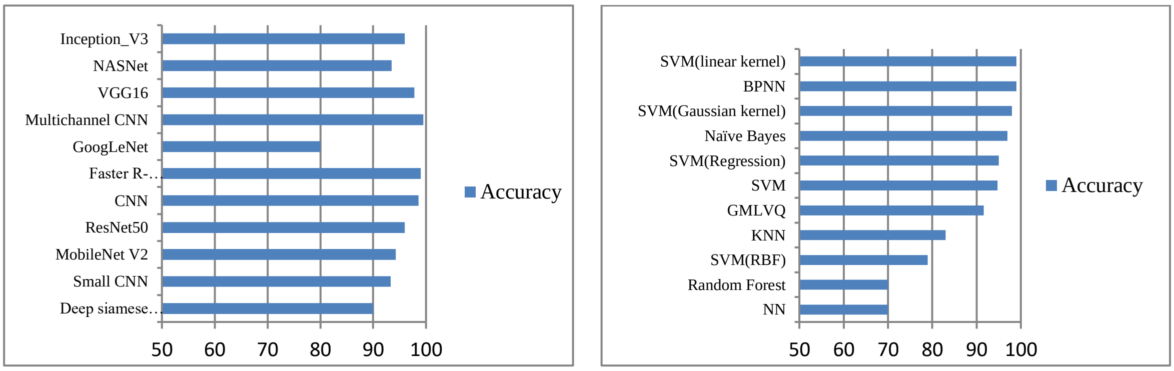
Two types of classification methods were used to classify crop leaf diseases: ML and DL. The important dissimilarity between traditional machine learning and deep learning methods is by means of feature extraction. In traditional ML, the features are not computed automatically whereas in DL the feature extraction automatically takes place and it is considered as learning weights. So, in DL the system itself learns the needed features by providing sufficient data. The most common machine learning algorithms used for classification of plant diseases are KNN, SVM, DT, RF, BPNN, NN, NB and ensemble learning. The frequently used deep learning algorithms present in the literature were CNN, CNN models which were Pre trained on ImageNet and used transfer learning.

Chowdhury *et al.* [12] proposed a plant disease detection and classification system, it uses transfer learning and deep feature extraction in. The authors were compared the obtained results of VGG16, GoogLeNet, ResNet50 CNN architectures with deep feature extraction by SVM and KNN. Experiment results shown that classification with SVM and ResNet50 given best results (98%) than the remaining combinations. The authors also compared the results of traditional machine learning algorithms i.e. SVM and KNN, SVM shown better accuracy (80.6%) than KNN (71.8%) but it is lesser than the proposed.

3. RESULTS AND DISCUSSION

It is observed from the Table 3 is the number of images used for the detection of crop leaf diseases by machine learning techniques are very less compared to deep learning techniques but generated remarkable accuracies." represents that the information is not mentioned in the paper. By using modified CNNs, optimized deep learning models and transfer learning models gives better results than the basic CNNs. Modified DL techniques gives better performance than traditional ML techniques. Modified CNN i.e. Multi-channel model gives highest accuracy [13] i.e., 99.5% in DL and SVM with linear kernel gives accuracy of 99% in ML techniques.

Figure 1(a) and Figure 1(b) represents the performance of the crop disease prediction system by using DL, ML techniques. The most used performance measures mentioned in the survey are accuracy, precision, K-fold cross validation technique for example k=10, recall, F1-score, sensitivity, specificity, dice similarity coefficient (DSC), minimum square error (MSE), and structural similarity index measurement (SSIM), categorical cross-entropy, Matthew's correlation coefficient (MCC) and leave one out cross validation scheme. Table 3 interprets the details of the various researches on crop leaf disease prediction and classification.



(a) (b)

Figure 1. The performance of the crop disease prediction system (a) performance of the DL techniques and (b) performance of the ML techniques

Table 3. Details of the surveyed papers for the detection and classification of Crop leaf diseases

Year	Reference No	Crop	Number of images	Number of Classes	Algorithm	Accuracy
2018	[14]	__	__	2	SVM, KNN, RF, NB, LR	58
2019	[15]	Multiple	800		SVM-Multi class	65
2018	[16]	Papaya	160	__	RF, SVM, LR, LDA, NAÏVE BAYES, KNN, CART	70
2020	[17]	Multiple	54305	27	Faster R-CNN with Inception Resnet v2	70.53
2020	[10]	Maize	3423	4	Naïve Baye's	77.46
2020	[12]	Grape	62286	5	Faster R-CNN, Inception-v1-ResNet-v2, SE blocks and RPN	81.1
2019	[18]	Mulberry	__	3	CNN	82
2017	[19]	Cotton	900	7	SVM (regression)	83
2020	[20]	papaya	10000	3	ResNet	85
2018	[21]	Tomato	1400	7	CNN	86.9
2018	[22]	Paddy	__		Alex Net	87
2018	[23]	Multiple	__	38	CNN	88.6
2019	[9]	Grape	130	4	Deep Siamese convolution network	90
2019	[24]	Potato	2465	2	Faster R-CNN	90
2020	[25]	tomato	4,671	3	MobileNet	90
2020	[26]	Multiple	148,775	38	Inception v3 transferred to target domain SVM	90.6
2020	[27]	Tomato	10000	10	CNN	91.2
2016	[28]	Cucumber	300	4	global-local SVD (single value decomposition)--SVM classifier	91.63
2019	[29]	Maize	100	4	CNN	92.85
2016	[30]	Alfalfa	899	4	SVM	94.7
2016	[31]	alfalfa	899	4	SVM, RF, KNN	94.74
2013	[32]	Multiple	500	30	SVM	95
2019	[33]	Wheat	8178	4	ResNet50	96
2018	[34]	Cassava	760	3	GMLVQ	97
2020	[35]	Multiple	54,305	38	VGG16	97.8
2020	[36]	Multiple	54,305	38	VGG16	97.8
2020	[37]	Maize	6866	5	Optimized VGG16	97.9
2020	[38]	Maize	6866	5	Ensemble model of two pre-trained CNN	97.9
2020	[38]		20,000	19	CNN	98
2019	[39]	Multiple	120,000		ResidualNet	98
2020	[11]	Multiple	54,305	38	Pre trained ResNet50,	98.2
2020	[40]	Maize	1152	3	CNN model with optimized trainable parameters	98.4
2019	[35]	Tomato	17929	10	CNN	98.6
2020	[41]	__	400		CNN (ReLu, Tanh, Softsign, linear, sigmoid)	98.8
2015	[5]	Tomato	__	__	SVM (linear kernel)	99
2017	[42]	Tomato	60	2	NN	99
2019	[43]	Banana	18,000	18	Faster R-CNN/SSD+ResNet50	99
2019	[44]	Apple	1192	4	Alex Net, Google Net and DenseNet201 Layer	99.2
2018	[45]	Multiple	85000	58	CNN	99.5
2019	[13]	Multiple	54000	38	Multichannel CNN	99.5
2018	[46]	Potato	300	3	SVM	__
2018	[47]	Lentil	300	2	LBP, HBBP (Brightness Bi-Histogram Equalization)	__
2021	[48]	Multiple	54,305	38	CNN	__
2016	[49]	Brinjal	__	4	ANN	__
2018	[50]	Soyabean	16207	9	CNN	__

4. LIMITATIONS AND FUTURE WORKS

The most common limitations of crop leaf disease prediction system based on visual symptoms are Lack of sufficient datasets mentioned in the papers since the PlantVillage is the only public dataset that is generated under controlled conditions. Some of the authors developed their own dataset but they are not giving the access to others to compare the results and PlantVillage dataset could not provide the images for the commercial crops like chili with abundant number of diseases. The second most common limitation is the method of developing the dataset by image acquisition and image preprocessing. The common problems are Un-even illumination, Clutter field background and real cultivation condition and other parts of the plant images were not used to detect the plant diseases. Thirdly, apply the knowledge of ensemble algorithms, tuning of hyper parameters and diversity of pooling operations [19]. Fourthly, the prediction system needs enormous resources if the prediction was based on deep learning methodologies [25]. So, there is a significance to develop squeeze models to run the application in mobile phones, drones, UAVs and robots.

The frequent future works were, to develop real time enormous images and classes of plant diseases. Crop disease dataset can be integrated to incorporate location, weather and soil data of the diseased plant to examine crop and yield monitoring in support of smart agriculture. The crop disease prediction system can be enhanced for detecting the plant diseases in large scale horticultural fields.

5. CONCLUSION

The system for identifying the crop leaf diseases can be developed in 5 steps. These are including Image acquisition; image pre-processing, image segmentation, feature extraction and classification. In this survey we analyzed various methodologies versus accuracies, datasets, crops, requirements of number of images and classes, also analyzed performance measures, limitations and future works. The conclusion of the study enhances the importance of integrating computer vision, machine learning, deep learning to the automated devices like UAVs, smart mobiles in the era of agriculture. More investigations, datasets have to be developed to detect the diseases at the instant time even if the yield is large scale and containing multiple diseases also, with the squeezable resources.

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