Techniques of deep learning and image processing in plant leaf disease detection: a review

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ABSTRACT

Computer vision techniques are an emerging trend today. Digital image processing is gaining popularity because of the significant upsurge in the usage of digital images over the internet. Digital image processing is a practice that can help in designing sophisticated high-end machines, which can hold the ophthalmic functionality of the human eye. In agriculture, leaf examination is important for disease identification and fair warning for any deficiency within the plant. Many prominent plant species are facing extinction because of a lack of knowledge. A proper realization of computer vision techniques aid in extracting a significant amount of information from leaf image. This necessitates the requirement of an automatic leaf disease detection method to diagnose disease occurrences and severity, for timely crop management, by spraying pesticides. This study focuses on techniques of digital image processing and machine learning rendered in plant leaf disease detection, which has great potential in precision agriculture. To support this study, techniques exercised by various researchers in recent years are tabulated.

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1. INTRODUCTION

Farmers’ revenue is an essential and important trait for any country. All the resources directly or indirectly are associated with agriculture and its product. Thus, improvement in agri-farm products becomes significant for the overall development of the country [1]. Plants are important food resources; they are also an important part of the food chain. Some medicinal plants are rare and extinct, which need to be preserved. Plant disease detection is an essential chore to maximize the farm productivity and survival of rare species. It is the basic imperative task, as the crop yield gets affected due to various plant diseases. Plant diseases are categorized as biotic and abiotic. Abiotic diseases are caused due to non-living things [2], [3]. Such as ecological circumstances, weather conditions, and spring frosts. Most abiotic diseases are preventable, least transmissible, not communicable, and harmless. Biotic diseases are caused due to living organisms such as bacteria, fungi, and viruses. Various forms of bacterial, virus, and fungi related plant diseases are shown in Figure 1. The most prominent diseases found in leaves are anthracnose, leaf spot, slow wilt, and quick wilt. Accurate disease identification is essential to assist in appropriate fertilizers usage [4]. Most of the research work done in the identification and classification of plants is based on their physical appearance. The traditional approach to diagnosing disease is based on the ideal laboratory conditions with limited resources [5]. For this, many factors are taken into account varying from plant length, appearance, leaf color, petals, stem, and root. It is realized in the given study that the plant's leaf is self-sufficient to provide reasonable details of the plants' complete health [6], [7]. Plant leaves are available throughout the year, are easier to be photographed digitally, and simpler to enumerate in two dimensions.

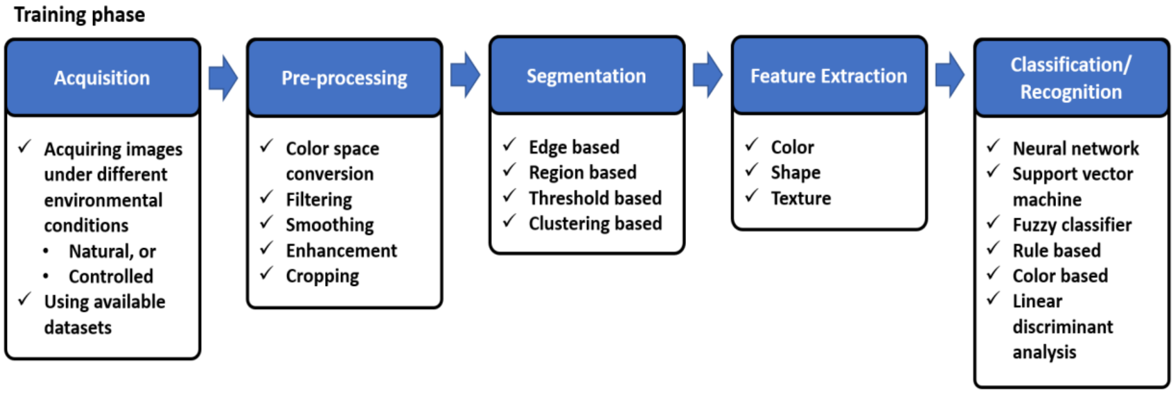

Figure 1. Digital image processing

2. METHOD

The main motivation for this research work is to provide a clear and precise understanding of the most prominent deep-learning methodology used in recent years in leaf disease detection. This study will help researchers to acknowledge various sources of data, devices used for gathering data, preprocessing, post-processing, and segmentation methods used in recent years. The comprehension is provided in the form of tables. The researchers should know the most successful methods used and how the said method performs.

To have a better understanding segmentation technique that provides high output are discussed with their advantages and limitations. Machine-learning techniques are classified highlighting outcome-based review, over the recent practice. Through this paper, readers would motivate to implement high-end techniques like deep learning for other plant diseases present in fauna flora not explored so far.

3. DIGITAL IMAGE PROCESSING

Digital image processing is a division of computer vision systems that helps in designing sophisticated high-end machines that can hold the ophthalmic functionality of human beings. It is a prominent field in agriculture for plant species detection, disease detection, biological processing, and many other scientific and engineering fields. Digital image processing is a systematic approach to digitizing the pictorial representation in the form of elements known as pixels. This includes enhancement, filtering, and segmentation [8]–[10]. The main aim of digital image processing is to enhance important parameters and compress irrelevant information about the object of interest. Classification of plants is required to segregate useful and not-so-useful plants. Plants classification done manually is laborious, time-consuming, and in the absence of an expert incorrect. This has influenced many researchers to conduct experiments to automate the process in the agriculture unit in its entirety. Agricultural sustainability in terms of productivity can be retained with steadfast precise techniques [11], [12]. There are wide techniques available in computer vision to provide better accuracy, precision, and recall faster than the traditional approach, which is the motivation to come up with this study. An effort is made to represent the review in a significant way. This paper is organized into sections that discuss the digital image process, machine learning techniques, and convolutional neural networks (CNNs) by segregating the relevant information in tabular form for clear vision.

Images are the pictorial representation, which we humans can view through the naked eye. Fundamentally, digital images can be represented in three basic type’s binary, grey, and red-green-blue (RGB) images. The secondary colors such as hue-saturation-value (HSV), YCbCr, L*a*b*, hue-saturation-intensity (HIS), cyan-magenta-yellow (CMY), greyscale, and CIE [13], [14] are color transformed as per the need of the experiment. The digital image represents many facets, extending from image acquisition, digitization, enhancement, or subsequent processing by exhibiting mathematical characterization for image display. Figure 1 shows the basic model of digital image processing with sample examples in each of the phases.

3.1. Image acquisition

Image acquisition is a process of data collection. Data acquisition is done using an online image repository [15], [16] or laboratory assessed. The most trending technique nowadays is live image capturing. This trend is emerging in agriculture, as there is a lack of datasets relating to the study of research interest [17]. Table 1 shows the image acquisition carried out by recent researchers systematically.

Table 1. Data sources and pre-processing techniques

Data set/source	No of images	Device	Back-ground	Pre-processing	Post-processing	Thresholding method	Reference
Real captured image	900	Digital Camera	Natural/Complex	Binary conversion	Thresholding	Histogram Based	[5]
Captured	560	Nikon Coolpix	Complex	HSV	Three different color space	Gaussian	[7]
Field captured image	720	Samsung	White paper	Automatic	Radial Map	Otsu	[8]
UoM	1320	Camera	White	Average F measures	MLBP	Otsu	[10]
Flavia, Foliage, Swedish	1320	Online	White	LBP	MLBP	Average F-measures	[10]
Captured	227	Camera	Plain White	Clustering	Binarization	Otsu	[14]
Dummy data	82	Created	NA	2-D Spatial	Erosion technique	Thresholding	[18]
In field	150	Digital camera and smart telephone	Gray	Denoising	SR based classification	PHOG	[19]
Online	75	Public repository	Plain	Denoising	Cluster	Otsu	[20]
Captured	4923	USB Camera	Black/White	Image Enhancement	Classifiers	NN	[21]
Plant village	~4309	Plant Village	Gray	Deep learning	NN Classifiers	Alex Net/ Squeeze Net	[22]
Satellite images	5932	Nikon DSLR-D5600	Gray	CNN	CNN	Neural networks	[23]
Camera captured	1443	Smart Phone/Camera	Complex	CNN	CNN	Neural networks	[24]
Plant village	1000	Digital camera	White	Gray level matrix	ReLU	Cost Matrix	[25]
Captured	5000	Camera, mobile device	hard negative	Image Enhancement	Deep learning/CNN	Meta Architecture of CNN	[26]
Plant village	54306	Online	Black	-N	-N	Grey Level	[27]
Plantvillage.org/	14,208	(Nikon Coolpix S3 100)	Complex	DCNN	DCNN	Deep neural networks	[28]
PlantClef2015	272892	Repository	Plain	CNN	CNN	GPU	[29]
Plant village	54305	Plant Village	Gray	K-NN	CNN	Deep learning	[30]
Captured	15620	Canon EOS550 D	White	CNN	C NN	ResNet	[31]
In field	150	Canon A640 digital camera	Complex	k-Means	PNN	PCA+ Neural networks	[31]
PPBC	1000	Repository	Complex	RPN	CNN	CV algorithm	[32]

3.2. Preprocessing

The purpose of image processing is to split an image into significant, non-overlapping regions. The major step in image analysis is segmentation. Before segmentation, images are pre-processed to remove noise i.e., unwanted disturbances. Preprocessing is the basis and primary procedure for training data individually for image processing. It is done by processes called smoothing or enhancement, color space conversion, and filtering [12]. It is the main step to enhance and improve the image vision. With high-end computing techniques plant, (crop) disease identification and detection could be realized indirectly [33]. The direct implementation method includes serological and molecular techniques. Which is done by a pathologist in the laboratory and by an agriculture-based researcher. Indirect disease detection diagnosis such as computer vision techniques is used to gain high throughput for large datasets [34]. Figure 2 depicts the process of disease detection in rice plants through digital image processing and testing. The quality of feature extraction and the result of image analysis using the image preprocessing method have a very intense positive effect [35]. It is corresponding to the mathematical normalization of the data set. Pre-processing is done in two steps, first to preserve pixels as it is, and second use filtering [36]–[38]. Preserving images, as it is results in a tedious analysis as all that images may be of varying size and parameters [18], [39]. Hence, a proper filtering technique is used to extract desired features. The general technique involves the conversion of one input feature to other output features [40], [41].

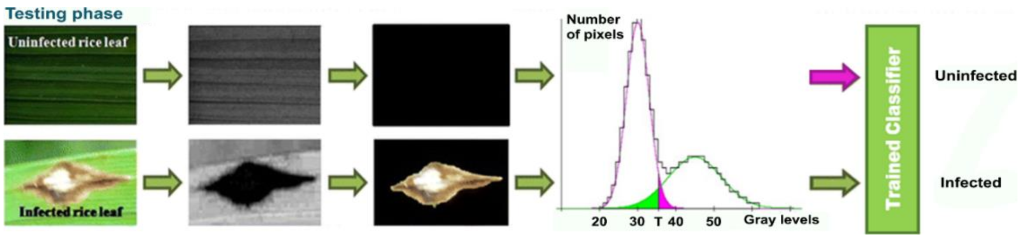

Figure 2. Phase of images testing of Rice plant leaf [3]

Other prevalent primary processing techniques involve translation in color expanses, procurements, leveling for filtering, and enrichment of specific features in the crop. Image conversion facilitates the removal of the shadow effect in the images taken under natural environment conditions [19], [42]. As per the review, the color image has a comparatively better image output than the grayscale. However, for diagnosis of leaf disease, RGB gives clearer and noise-free output compared to grayscale images [43], [44]. The dull or blur image needs to be brightened. The images are manipulated so that they are more suitable for the specific application [45]. Discrete cosine transform is a technique applied for leaf image enhancement. Enhancement is the process to brighten the stultified part of the image and give it a lively, clearer appearance like the original. Histogram equalizers are applied in plant leaf disease diagnosis as an image enhancer. The background removal process is simplified after an image is enhanced. Cropping is the basic practice to adjust images as necessary. Generally, the acquired image is either downloaded or taken in the real environment with the help of a camera. These images are not of the same size and resolution. It is required to change the aspect ratio of images to collectively form a dataset [46]. Cropping is a technique mostly used to eliminate peripheral unwanted noise or unwanted parts from the image. The concept called auto cropping can be combined with any other technique such as fuzzy clustering to form sharper classifications. Tools are available to crop images in rectangles, squares, polygons, and other forms.

3.3. Image segmentation

Pre-processed data are segmented through different techniques such as edge-based, region-based, threshold-based, and clustering-based. The focus here is to extract informative data from the pictorial representation [20], [47]. The images can be brightened, blurred, enlightened, changed contrasts or changed to another color format [21], [48]. During the segmentation procedure, the background of the image is crucial. Under a natural backdrop, the image is supposed to be complex. The distinction between the required and unwanted parts of the image becomes difficult. There are optimal chances that there will be hard negative features, which are not so-useful entities. So as good practitioners, researchers remove the background or convert the background image to white or black. Some papers, also suggest grey background to suit the choice of image color conversion done [49], [50].

3.3.1. Low level segmentation

Low-level segmentation is the segmentation done directly at pixel levels. The techniques used are thresholding, edge based, and region based.

a. Thresholding

Thresholding is a technique where an image is converted from one form to another form of color. That is from color to grey, RGB to HSV, RGB to YCbCr, RGB to CMY, grey to binary, and so on. This is done to reduce the noise as well as the shadow effect in the image. Otsu thresholding [22], [51] algorithm is one such age-old technique. The algorithm is very robust, and strong, and provides accurate results. Due to its high accuracy and clear differences, this is popular until today and is the primary choice among scholars.

b. Edge-based

To correct the periphery of the image contours, edge detection is done. In this method, the corners of the images are checked for any discontinuity or breakage [52]. This is the means of finding any default related to the image edge to differentiate one object from the other in the image. This method gives the boundary-related details of pixel intensities in the image. Lesion segmentation gives a significant result in cucumber leaf image diagnosis.

c. Region-based

The spot detection practice in unhealthy plant leaf diagnosis elevates the chances of rectifying and verifying the disease symptoms appropriately. The spot uncovering procedure can be based on regions separated as normal regions, spot regions, background regions, or growing regions. These techniques are crucial in segregating the disease from the core region. The region is narrowed down as a region of interest

[52]. The functionality of region-based segmentation is similar to edge-based segmentation. Here the neighboring pixels are also considered to form a group of pixels near to each other so that it stands out as a sub-region i.e. region within the image [53]. This region may further grow based on predefined criteria. Region-based color differentiation can be highlighted as that of undesired areas. Consider image f segmented into more homogenous regions $R_i, i = 1 \ldots n$. An *f* image can be segmented into regions R_i, such that:

$$f = U_i^n R_i$$
$$R_i \cap R_j = \phi, 1 \leq i, j \leq n, and\ i\ \neq j$$
$$P(R) = True\ for\ all\ i$$
$$P(R_i \cup R_j) = False\ , 1 \leq i, j \leq n, and\ i \neq j, and\ R_i\ , R_j\ are\ adjacent$$

where $P(R)$ is considered to the logical predicate well-defined over-all points in R space. This is true for the pixels inside the region and false outside the region.

3.3.2. High level segmentation

The segmentation process is ruminated at a high level when instead of pixels, direct objects of the images are considered. Such as clustering-based segmentation. These channels to the usage of the data at the larger level where instead of the object-pixel elements alone the neighboring pixel are also considered. Such that they form similar group elements and are formed as clusters [23], [54]. Clustering-based segmentation is like detecting similarities in the regions of the given image or image under test. Most authors have recommended k-means clustering for the segmentation of images. Some segmentation is done separately by means of mathematical Euclidean measurement of space difference. Zhang *et al.* [19] used orthogonal locally discriminant projection (OLDP) an orthogonal nonlinear dimensionality reduction algorithm for validating symptoms of plant disease. The clustered out-turn is fed to neural network classifiers. The segmentation techniques are cited in Table 2, which is reviewed through the reference papers.

Table 2. Segmentation methods reviewed in papers with advantage, limitation, and critical comments

Segmentation method	Segmentation level	Advantage	Limitation	Critical comment	Ref.
Otsu	Low	Clear thresholding	Wrong selection may result improper segmentation	Effective erosion operation	[8]
MLBP	High	High accuracy, nearest possible pixel difference	May sometime give nearest neighbor error	Effective for clustering techniques	[10]
Enhanced snowmelt runoff model (SRM)	Low	Better clarity and noise free	All colors need to be considered	RGB scale gives better clarity than gray scale	[12]
K-means	High/Complex	Better classification	Can only be applied for two or more classes	Gives clear generalization	[14]
Enhanced SRM	High	Better suited to human/ machine Interpretation	Works well with RGB image and not with grey scale	Suited for machine learning	[15]
K-means clustering	High	Easy to analyze	More number of clusters does not give accurate result	Maximum 3 cluster will give effective result	[33]
Binarization	Low	Extracts relevant information	Restricted application	Small imperfection details may not be visible	[18]
Ada-Boost	High	Accuracy similar to human vision	Differentiating background similar to disease symptoms difficult	Technique can be matched to human expert in real time	[42]
K-means, user pixel	Medium/fairly Simple	Enhances smoothening/ denoising	Sensitive to the initial centroids and the number of clusters	Only generates enhanced results when the initial centroids are close to the desired solution	[42]
K-mean clustering	High	Images clustered into different sectors	Not suitable for binary	Classifier model advent to cluster the images	[20]
HOG	High	Gives high accuracy	High computational power	High computation but with high accuracy	[55]
Deep networks	High	Faster processing	Pure background/Controlled environment	Laborious task, consume more time/may not be efficient	[56]
Region Growing	Low	Partition an image into regions	Seed regions are marked. Non-seed regions considered after repeated analysis.	Simple approach, determines whether pixel need to be added examining neighbor pixels	[57]

3.4. Feature extraction

The output from the segmentation stage is followed by the feature extraction phase. Feature extraction relates to either feature finding or feature description. This phase is useful to reduce the data size without losing its property. Feature finding has three major components as color, texture, and shape. Imaging techniques are brought into use to do online rectification. These processes use hyperspectral imaging [25], [58]. It is a non-destructive means to check medicinal plants in industries. Feature description gives more detail about the image, relates to the quantitative image attributes, and is very useful in detecting moving pictures its relativity is with the region or boundary of the image. This stage is important from a dimensionality reduction point of view, where the raw data is converted to manageable groups or chunks for further processing. This speeds up the processing methodology [26]. A fully connected layer in a neural network automates the process by acquiring large features from the training set without accounting for spatial features in the image in deep learning practices.

3.5. Classification

Classification in plant disease detection refers to symptoms and their pattern. Each disease in a plant has its specific pattern. Segmentation is considered to be the most difficult part of image processing as input to computer vision depends solely on the quality of the segmented output. For a few cases, partial classification is desired. Researchers have used color segmentation and used a self-organizing map for further classification, such as that for cucumber leaf disease detection and tomato leaves [52]. Visual analysis is simple and the least expensive. However, is not an efficient method. There are some areas where expertise is always advisable. Like in agriculture for plant disease detection. Where manual analysis may result in the wrong treatment of crops and the wrong usage of chemicals if not done by an experienced and expert person. Classification is finally the predicament where we start labeling or classifying images based on the basic extracted features [59], [60]. The use of deep learning with image processing has come out as a splendid combination to apply in such relative fields. Prominent machine learning algorithm implemented as classifiers are discussed in the next section.

4. MACHINE LEARNING TECHNIQUE

The ultimate aim of machine learning is to imitate humans. Machine learning is the science behind artificial intelligence where the machine learns from the available data, pattern, or pictorial representation just like a human does. Subsequently, the learning is implemented without human intervention [61]. When trained the machine learns on its own. Such learning helps in customizing a large number of data from the commercial database and reliably discovering knowledge from them. It is the fastest-growing field in computer science and has fast-reaching applications. There has been wide use of image processing and machine learning in monitoring leaves, harvesting, and some other phases of plants. The other prominent area in agriculture where machine learning is implemented is monitoring harvests. Automation in field-based disease diagnosis ensures benefits to plant breeders and growers [55], [62], [63]. This is done for disease detection, checking the invasion of insects, or for simply monitoring production. For the large site, unmanned aerial vehicles are employed [27], [56]. It is advisable to have early disease diagnosis in plants to reduce the total cost of expenditure in agriculture and overcome treatment associated with environmental influence. The benefit of using advanced techniques like machine learning with image vision is to have automated remote observing for precision agriculture where land coverage is huge.

Machine learning techniques are divided into two major paradigms, supervised learning, and unsupervised learning. In a supervised way, the machine is trained with labeled data and in an unsupervised approach, the data to be learned is not labeled. These two criteria are to confer programs with proficiency to learn and adapt to the given model. These two variants are discussed in the succeeding section. Based on the techniques of learning adaptability, machine learning is categorized as deep learning and shallow learning [64], [65]. Figure 3 shows the basic hierarchy.

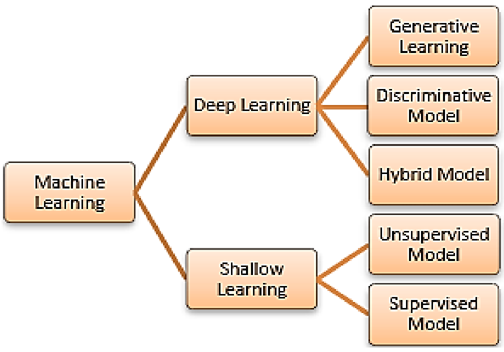

Figure 3. Machine learning hierarchical model

4.1. Deep learning

Deep learning is a prominent field. It is a model that can provide accurate, quick, and automatic classification. This is the reason deep learning has gained exponential popularity [28], [66], [67]. It has become an oppressive research topic among researchers. The deep learning model comprises input layers with a set of neurons, an output layer with a set of output neurons, and intermediary neuron layers. In deep learning architecture with input and output layers, there are various classifying/hidden layers that act as classifiers. The data under study for such a model is distributed as training and testing sets [29], [68]. Three major paradigms include the generative, discriminative, and hybrid models. The generative model, also termed parametric density estimation, is assumed generative because the data is considered to be of the parametric type whose value needs to be considered or understood. A generative model can be estimated based on maximum likelihood. This is a form of probabilistic estimation. For high-end usage, the probabilistic neural network is realized [29], [68], [69]. The equation for continuous random variable estimation considering the likelihood as log density (with the probability of X on x, where x is a random variable) is given

$$l(S;\Theta) = \log\left(\prod_{i=1}^{m} P_\Theta\,(X_i)\right) = \sum_{i=1}^{m} Log\, P_\Theta(X_i)$$

where S stands for training set, $S = (X_1 \ldots X_m)$, P_Θ = represent density distribution.

The discriminative model belongs to the conditional category i.e., logistical class model. Logistic regression, decision tree, naïve Bayes, and Gaussian mixture model are examples of such models. Here the classification is based on clear boundaries. The direct map is formed for unobserved variables or the target under study. Multiple instance techniques are used in an unsupervised learning environment. A complete batch of data is considered instead of the instances [69], [70]. Under supervised learning, there is a way to predict (*input*)*q* on future (*output*)*p*. If pi is considered as given features of the data points and let *qi* be the corresponding labels. A function f is set out with relevance to (pi, qi) that considers *p* as input and results in *q* as output. Such a model can be considered discriminative. Support vector machine (SVM), k-means clustering, and maximum of traditional neural networks are discriminative models, like multi-layer perceptron, convolution neural network, and probabilistic neural network explored in most papers. Hybrid deep-learning models are formed when machine-learning models are integrated with other models to enhance output or to improve expected output. The resultant model is a hybrid model. The model combination can be soft computing based or optimized [30], [71]. The hybrid model relates to advanced machine learning techniques. Bagging and boosting techniques are grouped to form the ensemble method, which is a hybrid model.

4.2. Shallow learning

The deep learning model is a machine learning technique that refers to unstructured data and is based on self-learning, whereas shallow learning is a technique based on structure or labeled data. Shallow learning includes supervised learning and unsupervised learning technique. This technique is similar to a neural network, but the working layers are just one or two layers [31]. Low-dimensional features are extracted, and the complexity is less as the data size is moderately small. Supervised learning is the most common and widely used environment in machine learning methodology. The algorithm is implemented in a model where input and output are predefined [72]. Supervised learning can be further classified as a classification model and regression model. The supervised classification model consists of methods like SVM and random model. Unsupervised learning is quite opposite of supervised learning. Unsupervised learning is a procedure where machines are made to learn by themselves. It is an algorithm where machines are made to understand the pattern and interpret the desired output by determining and providing correct classification. To be used for prediction purposes later [73]. The main type of unsupervised-based learning algorithms is principal component analysis and clustering. Clustering can be soft computing-based, hierarchical-based, graph theoretic-based, and partitioning based. Hierarchical clustering can be based on a divisive and agglomerative approach.

4.3. Convolutional neural network

A convolutional neural network (CNN) is an advanced algorithm in deep learning in the amalgamation of computer vision. It is a multilayer paradigm where each layer consists of a network of neurons. Each neuron represents the weight and biases associated with the object under observation. It is the most efficient practice for a huge data set. CNN is a robust technique to extract the important feature when the data size is humongous. It reduces the parametric count of the populated variable. Because of this reason, CNN is the popular neural network. CNN is well suited for image processing the reason being is, it provides better fitting with condensed parameters. CNN model is applied in classing disease in maize plants and in histogram techniques to demonstrate its importance. For tomato leaf disease identification primary CNN models such as Alex Net, Google net, and ResNet are implemented [28], [55]. This network can be trained very well to fit in sophisticated image analysis [32]. Table 3 summarizes prominent machine learning techniques implemented over recent years as per the reference papers. The main purpose of the work is to tabulate the data for better visibility of the work done in recent years. So that all the relevant data associated with techniques in plant disease detection is highly available.

Table 3. Summary of machine learning classifiers implemented in the study carried out in this paper

Machine learning classifiers	Accuracy in %	Features	Device/data source	Training data	Testing data	Validation data	Reference
SVM, Neural Network	80	Edge and color	Lumia 500/Sony Xperia XA1/Field	22	56	6-8	[4]
SVM/RBEN	90	Edge, color, texture	Digital Camera/Field	900	300	100	[5]
MLP/SVM	99/98.8	Morphological, Texture	Plant Repository	1200	800	400	[6]
CCF	97.29	Comprehensive color features	Nikon Coolpix/Field	93	93	93	[7]
Random Forest	90.1	Length, width, perimeter, area, no of vertices, color, perimeters, area of hull	Camera/Real field Images	510	129	50	[8]
BPNN	98.2	ROI	Digital camera/Field	-N	-N	-N	[9]
SVM	96.6	Geometric Features, color, texture	Created	64	64	64	[18]
context aware SVM	92	Color	Digital camera/Field	150	50	50	[19]
K-mean clustering	75	Color and texture	Public repository	75	25	25	[20]
Deep Learning	95.65	Auto Identified	Plant Village	54309	80%	20%	[22]
DECIML	65	Edge/Angle of token	Plant Village	45	20	20%	[53]
Supervised Kohonen Networks	81.65	Map Models	Satellite Data	7798	1000	1000	[54]
CNN	78 to 79	Auto generated	bcch.ahnw.gov.cn	5932	200	800	[23]
9 CNN classifiers	94.56	Color, shape, texture	Smartphone/Camera/Fiel d	1433	1012	433	[24]
CNN	95	Shape and Texture	Plant Village	4000	2000	1000	[25]
CNN	86.2	Special Features	BBCH 12-16	10413	10413	-N	[62]
CNN	98	Auto generated	Nikon D5300/Field	4742	250	180	[63]
ANN/CNN	95.5	Histogram of gradients	Flavia Data Set	630	135	135	[55]
VGG-VD16	97.95	Local Features	WDD2017	9230	7384	1846	[55]
Dense Net	99.75	Auto generated	Plant Village	34727	10876	8702	[27]
VGG –S	95.12	Local Features	WDD2017	9230	7384	1846	[56]
CNN	97.14	Colors & textures	ImageNet, Plant Village	54306	60%	40%	[65]
CNN	81	Disease Symptoms	https://www.digipathosre p.cnptia.embrapa.br/	50000	40000	10441	[66]
DCNN	93.4	RGB, HSV, L*a*b*	Plantvillage.org/forestry images.	8628	2292	3288	[28]
CNN	68.9	Auto selected	ImageNet	50000	272892	66711	[29]
Caffe	95	Auto selected	PlantClef2015	50000	272892	66711	[29]
K mean Cluster	89	RGB, HSV	In-field image	38	39	29	[57]
PNN	91.08	Statistical, Meteorological	In-field image	100	50	50	[57]
VGGNet-16	98.44	Colors and texture	In -field image	15670	11533	4137	[30]
Deep Learning	96.46	Texture, color, shape	Plant Village	55,636	1950	3900	[30]
CNN	88.7	Edge and curves	Camera/Plant Village	45000	3663	-N	[72]
PD^{2}SE-Net	98	Auto generated	www.challenger.ai	23381	23381	3422	[73]
RPN	83.57	Texture, shape, color, motion-related attributes	Repository	4714	1000	-N	[32]

5. CONCLUSION AND FUTURE WORK

The work displays segmentation, machine learning classifiers, and deep neural networks implemented in plant disease detection in tabular columns. It is observed that the traditional approach of managing the crop field is similar for most of the cases. This leads to uneven distribution of pesticides in the fields resulting in disease mishandling. Though diseases can be predicted based on climate conditions still their symptoms cannot be judged. According to this review, the most prominent segmenting techniques used are k-means, Gabor filter, and enhanced snowmelt runoff model (SRM). Conventional edge detection techniques include canny edge detection, Sobel edge detection, and Otsu method. Otsu is an age-old technique still staunch.

Real field/camera captured, online resources, and dummy data are the three major plant image data resources. The major drawback in image analysis is the complex/busy background when images are taken under real natural conditions. Plant leaves are self-sufficient to provide vital information, such as disease incidence, prevalence, and severity. Interactive region growing segmentation techniques can be employed for spot detection in plant disease. In the future, relevant techniques can be proposed to get an extensible set of disease extraction such as the number and area of disease spots. Global features or zone-based features can be explored. A collection of multi-angle images can be ruminated to overcome data inadequacy.

There is great real-world worth of machine learning algorithms and image processing techniques. According to the work it is observed that the deep learning-based implementation is less investigated in depth. This area could be further explored. The deep learning-based methodology could be used to speed up the process when huge data are involved. The accuracy acquired using the CNN model is 94 to 98%. Deep learning-based CNN models like VGG-16 and VGG-S can be implemented to extract higher significant accuracy to provide sharp, quick, and automatic classification. Fuzzy clustering techniques can also be comprehended for disease detection in plants.

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