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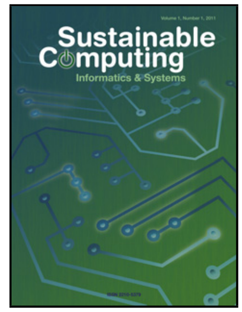

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Use of Deep Learning Techniques for Identification of Plant Leaf Stresses: A Review

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Abstract

The use of deep networks in agriculture has increased enormously in the last decade including their use to classify different plant leaf stresses. More recently, a large number of deep learning-based approaches for plant leaf stress identification have been proposed in literature but there are only a few partial efforts to summarize different contributions. Hence, there is a dire need of a detailed survey compiling techniques used for identification of leaf stresses found in a variety of plants. This work presents a review of 45 deep learning-based techniques recently proposed for 33 different crops using 14 famous convolutional neural network architectures. The techniques reviewed were divided in vegetables, fruits and other crops on the basis of stress type, size of dataset, training/test size and the deep network used. The effort will facilitate researchers especially those who are new in this field to get a quick introduction of the trend on using deep learning in plant leaf stress identification.

Keywords: deep networks, plant stress, agriculture, image processing

1. Introduction

Agriculture has always been the mainstay of life for all living beings. With the increasing world population, the need to improve the quality and quantity of crops has gained significant importance. The use of modern tools, especially based on information technology, has enabled humans to achieve this goal to a great extent almost all over the world [1]. But this benefit is achieved at the cost of increased number and types of crop stresses [2]. Stresses of leaf form a significant subset of the total set of plant stresses. Early detection [3, 4] of plant leaf stresses enables farmers to apply proper treatment and adjust quality and quantity precisely. In most parts of the world, leaf stresses are detected using field surveys which is a time-consuming process and is prone to error. Moreover, special skills are required to point out infected leaves in the field. This gives rise to the need of automatic methods to detect infected leaf in a crop and identify their different types [5]. The automatic methods bring several benefits such as early diagnosis of a stress enabling farmers to take preventive measures, detection, and identification for corrective measures and making the job of field surveyors easy. Among many automatic techniques, image processing based methods offer the most obvious solution to this problem [6, 7]. During the last decade, various types of image processing based detection and classification problems have been successfully solved using end to end deep learning-based models [8]. Deep learning has also found its way in agriculture and has been applied to a large variety of problems in recent years including identification of weeds [9], classification of land cover [10], recognizing types of plants [11], fruits counting [12] and plant leaf stress detection, etc. [13, 14]. Deep networks refer to a class of artificial neural networks [15] with multiple hidden layers between input and output layers [16]. With the availability of GPUs, the use of deep networks for various image processing applications has enormously increased [17].

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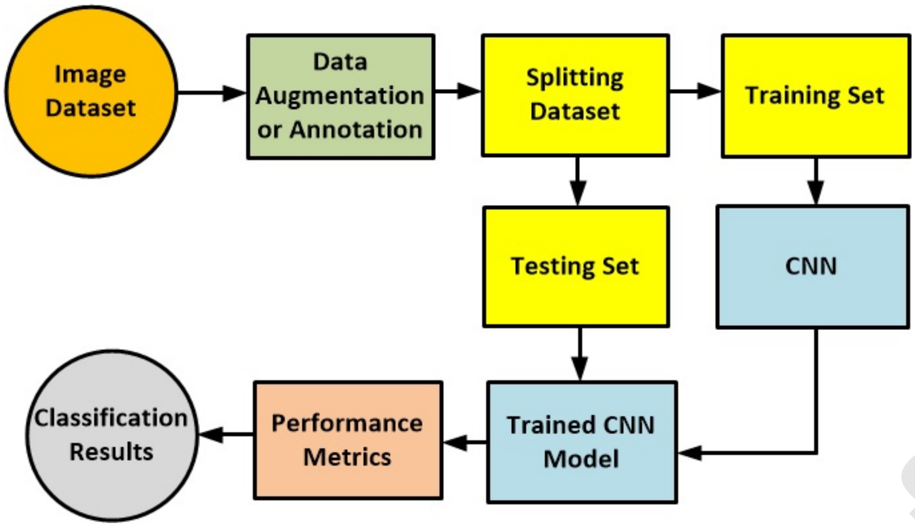


Figure 1: Block diagram of a deep learning based plant leaf stress recognition model.

Figure 1 shows various building blocks of a general deep learning based technique for plant leaf disease recognition whereas Table A.1 gives explanation of different abbreviations used throughout this paper. The input dataset usually undergoes some preprocessing e.g., contrast enhancement, normalization or data augmentation etc. The final dataset containing typically thousands of images is then split into training and testing portions. The training data (usually 70% to 80%) of the total dataset is used to train millions of parameters of a deep network. This time consuming step is typically performed with the help of an easily accessible parallel computing hardware called Graphical Processing Unit (GPU). The trained model is then tested on left out test data (usually 20% to 30%) to estimate the performance of the learned deep model.

The availability of a large number of recently proposed deep learning-based techniques for various plant stresses is the principal motivation behind this work. In the literature, we find several survey articles on plant leaf stress identification using image processing techniques. A recent article [13] presented a broad survey of deep learning-based techniques in all subfields of agriculture including plant leaf stresses. Another survey on plant fruit and leaf stresses using conventional feature extraction and classification based models was proposed by [6]. A comprehensive review of deep learning-based methods with emphasis on different Convolutional Neural Network (CNN) models was presented in [18]. However, their focus is on the use of different network architectures with little attention towards stresses of various plants. Keeping in view these efforts, we feel that there is a serious deficiency of a well compiled detailed review of leaf plant stress classification techniques based on deep learning.

This paper presents a survey of different deep learning-based techniques proposed for leaf stress related to various vegetable, fruit and miscellaneous plants. We have compiled only end-to-end deep learning-based methods proposed in recent years to detect infected leaf in an agricultural field for stress identification. In this review, 14 famous convolutional neural networks and their modified versions have been discussed for 33 different crops based on the type of plant, collection of data, preprocessing scheme, training & testing, evaluation metric(s) and the performance in a comprehensive tabular form.

The rest of the paper is organized as follows: Methodology to short list research papers to be included in this review is discussed in Section 2, a comprehensive introduction of different types of leaf stress(es) found on various plants are given in Section 3 with snapshots from real world field images. Section 4 summarizes the use and effectiveness of deep learning-based models in image processing including applications in agriculture and plant leaf stresses. Section 5 provides details of different relevant datasets reported in literature. Section 6 gives detailed comparison of 45 different techniques on the use of deep learning for leaf stress identification of various plants along with a discussion on network and training & test bifurcations

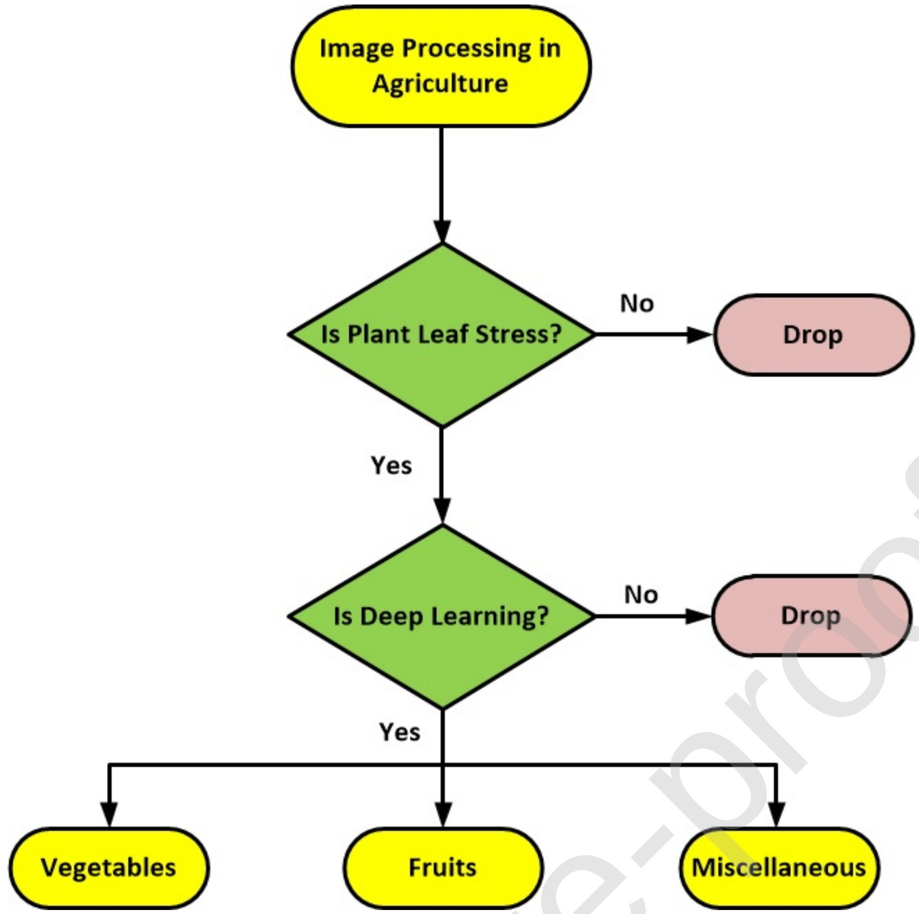


Figure 2: Graphical depiction of the methodology adopted to select papers to be included in this review.

along with the use of data augmentation. Section 7 provides discussions on commonalities & differences among techniques in addition to challenges, future directions and conclusion of this research work.

2. Methodology

In order to carefully select only the research papers addressing use of deep networks for plant leaf stress recognition, we used a step by step approach graphically represented in Fig. 2. Highlights of the procedure are given as follows:

- First of all 100+ research papers discussing image processing applications in the field of agriculture were collected with emphasis on recently published stuff. Scholar databases like Sciencedirect, IEEE Xplore, DBLP and Google scholar were used for this purpose.
- The list was reduced to 65 references removing the papers discussing conventional machine learning techniques in addition to review papers.
- In the next step, papers discussing image processing based applications for plant leaf stresses were retained.
- As the second last step, 45 recent papers proposing deep learning based solution for plant leaf stresses were taken to the final step.
- Finally, all the selected papers were subdivided in three categories 12 papers related to vegetables,14 related to fruits and rest 19 were cited in miscellaneous category.

3. Plant Leaf Stresses

Plant pathogens are a big concern for agriculturists all around the world. Pathogens are organisms responsible for the majority of plant stresses. Based on the type of pathogens, the stress can be categorized as either biotic or abiotic [19, 20].

3.1. Abiotic Plant Stresses

Abiotic plant stresses are caused by non-living agents such as ecological circumstances, weather changes, chemical usage, and nutrient deficiency [21]. All these stresses are non-infectious, non-transmissible and consequently less dangerous. These abiotic factors still hinder the growth of the plant without showing any significant symptoms. Fortunately, abiotic stresses can easily be avoided by eliminating causes like inappropriate soil moisture and shortage/excess of any nutrient etc. [21]. Sometimes dying plant tissues are attacked by pathogen and then finally come up as an infectious biotic stress [22].

3.2. Biotic Plant Stresses

Biotic plant stresses are caused by living organisms such as bacteria, fungi, pests and viruses etc. The affecting organism continues to develop itself on the nutrients of the host plant. Biotic stress cycle needs three factors for the pathogen to infect and grow:

- Vulnerable plant (host)
- Favorable environmental conditions
- Pathogen(s)

Plant stress cannot develop if any of the three i.e., susceptible host, favorable environment or pathogen does not exist. Moreover, a plant can be affected by more than one stresses at a time. Figure 3 shows a graphical summary of biotic plant pathogens.

3.2.1. Fungal Stresses

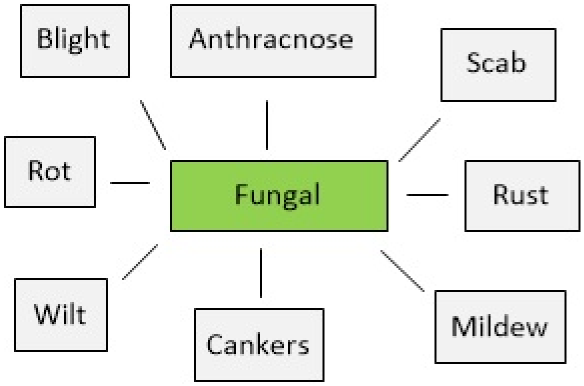
A wide range of literature addresses this class of stresses [23, 24] because they constitute two-third of total biotic stress. In literature we find around 1,900 types of fungi, snapshots of a few stresses caused by this pathogen are shown in Figure 4. Since fungi reproduce and spread quickly they are the focus of plant stress experts today. Almost all cash and food crops are affected by one or more types of fungal pathogens.

3.2.2. Bacterial Stresses

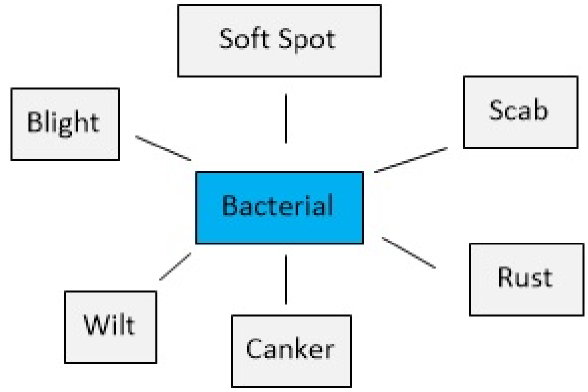
Almost 20% of the plant stress are caused by bacteria. They typically attack the plant wounds caused by any unfavorable condition and then multiply. Bacteria spread through rain, insects or wind. Some common bacterial pathogens are scab, soft spot, wilt and bacterial blight. Sample images of few bacterial stresses are given in Figure 5. Sometimes, bacterial stresses are further categorized on the basis of symptoms they produce and type of host invaded [26].

3.2.3. Viral Stresses, Oomycetes and Pests

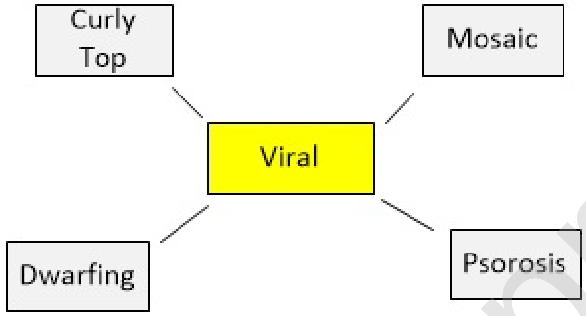
Some common viral stress are mottling distortion, curly top and dwarfing. Sample images of different viral stress are shown in Figure 6. They are considered to be less infectious and are found rarely in fields. Oomycetes are fungi like organisms found on susceptible plant. Their presence can be devastating if conditions are favourable. Downy mildew is the mostly commonly found oomycetes.



(a) Fungal stresses



(b) Bacterial stresses

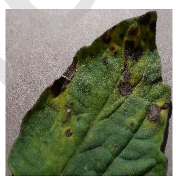


(c) Viral stresses

Figure 3: Classification of fungal, bacterial and viral plant leaf stresses

(a) Anthracnose

(b) Powdery mildew



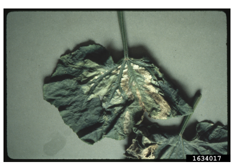
(c) Early blight

(d) Leaf spot

Figure 4: Sample images of fungal leaf stresses [25]

(a) Bacterial spot

(b) Bacterial canker



(c) bacterial wilt

Figure 5: Sample images of bacterial leaf stresses [25]

(a) Curly top

(b) mosaic

(c) Dwarf mosaic

Figure 6: Sample images of viral leaf stresses [25]

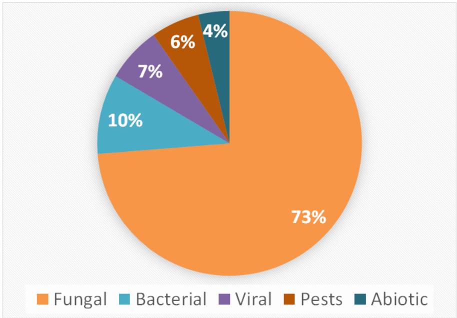


Figure 7: Summary of different biotic and abiotic stresses discussed in this review.

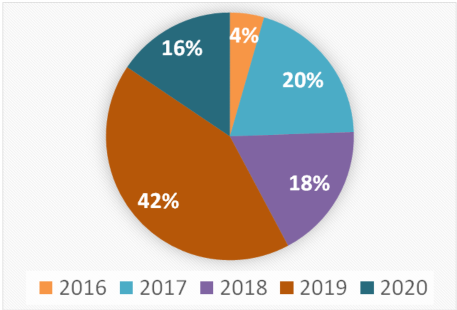


Figure 8: Year wise distribution of deep learning based research papers addressing plant leaf stress recognition problem.

This review presents a survey of deep learning based identification of various biotic and abiotic stress found in plant leaf. Pie chart given in Fig. 7 gives percentage of various types of stress covered in this research. Fungal stress constitute the larger part (73%) whereas bacterial form 10% of the total stress. Abiotic stresses caused by low nutrition and other environmental factors represent only a small percentage (4%) of the stresses surveyed for this review. Moreover, the pie chart given in Figure 8 gives year wise distribution of research papers included in this study. It is evident that the use of deep learning for plant leaf disease recognition is a growing field with number of research contributions increasing with every passing year. It should also be noted that this survey includes research papers available till March 2020. Therefore, in the pie chart, the number of research papers in year 2020 is lesser than it was in year 2019.

4. Why Deep Learning?

Deep learning has been a topic of discussion in image processing based applications for the last two decades [8]. Most recently its use in various agricultural applications has risen enormously and plant leaf stress sub-field is also of no exception [13]. We find several recent efforts in this area due to many advantages posed by deep learning in the field of image processing based applications. Some obvious advantages of these techniques are listed as follows:

- The approach allows to develop end to end feature learning-based solution and hence simplifying the proposed architecture.
- Automatic feature learning based on available data instead of trying different handcrafted features and then selecting the best for a particular application.
- Availability of a large number of pre-trained CNN-based models makes the development work quick and easy. Just modifying/retraining the final few layers optimizes the given network according to the targeted application and hence time and effort to train the whole neural network model can be saved.

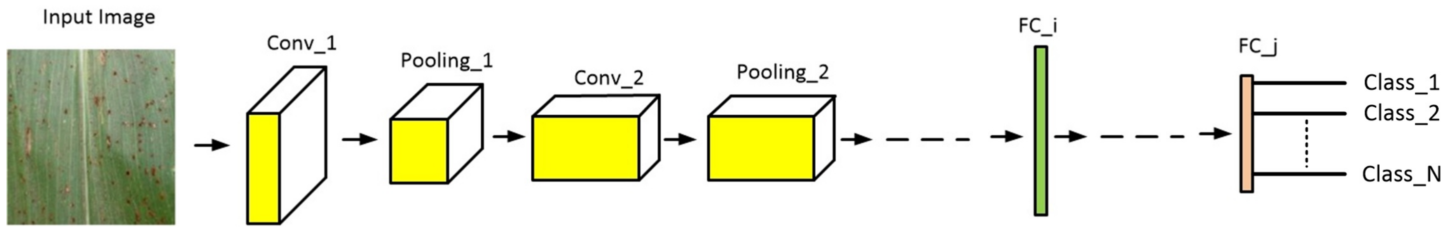


Figure 9: A typical CNN architecture for multi class plant leaf stress recognition

- Availability of free software packages (e.g., higher-level APIs in Python) in addition to access to widely used datasets makes it a choice for both beginners and experts in the field.
- Availability of high end graphical processing units (GPUs) including online access to Tesla K80 GPU provided by Google Colab. The GPU contains 12 GB RAM and is available free of cost for a single 12 hours session.

The use of deep learning, however, has some disadvantages compared to conventional manual feature extraction based techniques [16, 27]. The first and the most important disadvantage is the requirement of a huge amount of training data containing a large number of samples from each class (i.e., balanced). Secondly, a huge amount of training time even with the help of specialized parallel computing hardware i.e., GPUs [28]. Transfer learning is a technique widely used to address the above two disadvantages. Using this approach, a pre-trained deep network is modified such that the final few (mainly one or two) layers are re-trained keeping the remaining structure as such. Transfer learning [29, 30] is suitable in cases where we have either limited training data or can not afford hours/days of long training.

4.1. Convolutional Neural Networks (CNNs)

As mentioned earlier, deep networks [31] are called deep because they contain more than one hidden layers between the input and output layers. CNNs are the most famous type of deep networks in image processing based applications. The wide use of parallel computing hardware and the availability of a free development platform have given the use of CNNs in almost all image processing applications a boost during the last decade. CNNs consist of repeated convolutional, non-linear Rectified Linear Unit (ReLU), and pooling layers which make it a deep network. A typical convolutional neural network architecture is shown in Fig. 9.

Convolutional layers perform a conventional convolutional operation on the input image(s) but the coefficients of convolutional masks are learned during training. ReLU introduces a non-linear layer that gets rid off the negative values without affecting the convolutional or pooling layers. Mathematically, for a number x fed to a non-linear function, the output $f(x)$ is:

$$f(x) = max(0, x) \tag{1}$$

Pooling layer most of the time averages or finds the maximum in a small portion of the image to avoid overfitting and for translation invariance. Pooling layers have no parameters to learn during training. Like the ReLU, even the pooling layers have to learn nothing during training. However, the last layer(s) consists of a conventional fully connected neural network. Fully connected refers to the fact that every output from one layer is connected to each neuron in the next layer. Depending on the complexity, a large number of parameters are to be learned in this layer.

CNNs have largely been used to identify plant leaf stresses caused by different biotic and abiotic factors. In Section 7, we have discussed the frequency with which different pretrained deep learning architectures have been used by researchers in this field. These network architectures have initially been trained on millions of images to learn hundreds of thousands of parameters. For the sake of this particular applications, these networks are fine tuned on the available training data and hence saving the computational cost of training the network from scratch [13].

5. Plant Leaf stress Datasets

The use of deep learning imply a large amount of data for training the model. Usually, having tens of thousands of images is common to achieve good accuracy. Among other problems associated with plant stress recognition, collecting huge amount of real world field data is a big hurdle [32]. The common technique used by researchers to overcome this issue is to perform some suitable preprocessing. This operation augments original dataset with large number of translated, scales and inverted images etc. [6]. Moreover, annotating field images to know the ground reality requires the advice of an expert pathologist which also incurs additional cost. Images captured under varying lighting conditions also pose a challenge. Review of literature reveals that there are only a few widely and publicly available benchmark databases pertaining to plant leaf stresses. Table 1 contains details of five widely used datasets found in many current research contributions.

5.1. PlantVillage Dataset

PlantVillage is perhaps the most widely used dataset in the area of using computer vision to identify plant leaf stress [33, 34]. A large number of recent papers on plant leaf stress use either solely this dataset or merge it with their self-collected field images. PlantVillage is a nonprofit project at Penn State University in the US and Switzerland. It continues to collect tens of thousands of images from stressed and healthy crops. The dataset contains 82,161 leaf images from 24 different plants divided into 55 categories. Most of the researchers have used plantVillage as their image source to train, test, and validate data. However, the images have been captured under varying lighting and background conditions posing further challenges for researchers. The dataset is further divided into Plant Leaf_1 (images with cluttered background), Plant Leaf_2 (both clean and messy background images), and Plant Leaf_3 (mixed images) classes.

5.2. Digipathos Dataset

Digipathos is another widely used dataset in the field of plant leaf stress identification [35]. The database contains almost 3,000 digital photographs of main cash crops such as soybeans, coffee, rice, beans, wheat, maize and other fruit species. The database is free and publicly available for use in technical, academic and research studies. It was created with the aim of becoming a benchmark for plant leaf stress identification. The idea was to include symptoms and detailed descriptions of the causes and consequences of each stress. All the images in the database are labeled by experienced Botanists as ground truth.

5.3. Wheat stress Database

The Wheat stress database [36] was developed as a campaign which lasted for three years 2014, 2015, and 2016 in the fields of Spain and Germany [37]. The images were collected by several cameras and mobile devices in field conditions. The image acquisition process continued for whole season so as to get stressed leaf images at different cultivation and germination stages. The database covers three type of wheat leaf stress and one class of healthy leaf.

5.4. Coffee Leaf Dataset

The database comprises of Arabic coffee leaf images collected by [38, 39]. The image database not only presents images of four type of biotic stress and its severity in coffee leaf but it also segments symptoms from original leaf. A total of $2,147$ symptom images were collected. The dataset is publicly available on open source platform GitHub.

5.5. NLB Public Dataset

Images of maize healthy and stressed leaves collected by [40] are placed on Bisque Cy verse platform which is an open source web platform for exchange of different types of data sets. The images of healthy and stressed maize leaves were collected. A total of $1,834$ images were collected in the span of several days. The database also contains augmented images and lesions for future researches.

Table 1: Description of famous plant leaf stress datasets

S/N	Dataset	Total images	No. of Plants	Stresses
1	PlantVillage Dataset [33, 34]	82,161	24	55
2	Digipathos [35]	50,000	21	171
3	Wheat stress Dataset [36]	8178	1	4
4	Coffee Leaf Dataset [38, 39]	1747	1	5
5	NLB Public Dataset [40]	1834	1	2

6. Comparison of Leaf stress

In this section, we present a comparison of different deep learning techniques proposed for various plant leaf stress in recent years. Tables 2,3 and 4 list a grand summary of different leaf stress specific to different vegetables, fruits and miscellaneous crops. Corn/maize, tea, cucumber, wheat, tomato, apple, banana, cassava, radish, olives, soybean, sugar beet, mango, ginkgo tree, walnut, coffee, cherry,strawberry and potato etc are the main crops surveyed in this research. Next, we present a detailed survey of deep learning based identification techniques proposed for leaf stress pertaining to these plants.

6.1. Vegetable Leaf stresses

This review discusses several different types of leaf stress related to seven vegetable plants namely, maize/corn, cassava, sugarcane, radish, olives, soybean and sugar beet. A detailed survey of different deep learning based techniques for these crops is given in Table 2.

Maize/corn is a widely grown crop worldwide [41]. It is one of the crops most vulnerable to many biotic leaf stress. The plant suffers with mainly nine different types of leaf stress. Table 2 presents details of five different deep learning based technique related to this crop addressing different number of plant stress. The works proposed by [42, 32, 43] address nine and eight stress respectively using improved versions of GoogleNet, CIFAR10, Inception V3 and Inception V4. But the other two techniques experimented with lesser number of stress [40, 44] using VGG16 and VGG19 deep networks. The work presented by [42, 43, 44, 32] fine tune pretrained models but the one given by [40] trained a deep learning model from scratch. It is interesting to observe that transfer learning based approach demonstrated dual advantage here i.e., it took lesser time to be trained on a GPU in addition to being around 2% more accurate compared to the network trained fully on training data. All techniques have either used the famous PlantVillage dataset, Digipathos dataset or the images were collected as a result of field surveys by respective authors. Use of GPU is also common irrespective of the use of transfer learning or training from scratch.

A transfer learning based method on cassava vegetable was presented by [45]. The technique used Inception V3 model on a dataset containing $15,000$ images and obtained an accuracy equal to 93% and compared its results with conventional machine learning based models like SVM and KNN.

Figure 10: Coffee leaf lesion and spot extraction [38]

A VGG based model for making a binary decision regarding presence of a stress on radish plant leaf was suggested by [46]. The dataset comprising of $2,062$ images was collected using an Unmanned Air Vehicle (UAV). Region Of Interest (ROI) was selected manually and the data was divided into two classes namely healthy and stressed leaf. A VGG-X model was trained with the help of a 12GB TitanX GPU using Caffe framework. The trained network was found 94% accurate on left out test data and outperformed various standard machine learning algorithms.

6.2. Fruits Leaf stress

In this survey, we discuss leaf stress related to six different types of fruits namely, cucumber, tomato, apple, banana, grape and mango. Details of these techniques is given in Table 3. Cucumber is a widely grown crop all over the world. Table 3 gives review of two deep learning based techniques reviewed for this research. The technique used by [52] uses a modified form of AlexNet CNN using Tensorflow platform on Nvidia GPU. The accuracy using this technique was found to be around 99% for six types of cucumber leaf stress. Another recent work on the identification of five leaf stress was presented in [53]. The research work mainly addressed stress found in cucumber plant namely scab angular, powdery mildew, anthracnose, scab and downy mildew. A simple modification performed by training three different CNNs on three channels i.e., R, G, B produced promising results. Each network was composed of ten layers including three convolutional and pooling layers each. The algorithm was implemented in MATLAB on a bunch of self-collected data. The recognition results were found to outperform conventional feature extraction based methods and famous Support Vector Machine (SVM) classifier.

For the sake of this review, we discuss four techniques related to tomato leaf stress [54, 55, 56, 57]. Ashqar et al., [54] trained a convolutional neural network from scratch on PlantVillage database whereas the other three contributions made use of pretrained networks through transfer learning. Table 3 shows that different preprocessing techniques like augmentation, annotation and scaling etc. have been applied in all reported works.Fuentes et al., [55] applied several augmentation techniques on their self collected data before it was used to train three CNN models. This preprocessing step worked to enhance bother inter-class and intra-class accuracy on test data.

Five classes of apple were identified using a deep network in [58]. The training data contained around 11,000 images used to train the deep network which was finally tested using 2,801 images. The work was found to outperform conventional classifiers e.g., SVM in terms of classification accuracy and convergence rate. A method comprising of pre-trained and trained from scratch CNN based models was proposed by [29] to identify four severity levels of apple leaf stress. In order to save

Table 2: Summary of deep learning techniques surveyed for vegetable plants leaf stresses.

Plant	Year	Ref.	Stresses	Preprocessing	Network	Software	GPU	Dataset	Training	Testing	Accuracy	Comparisons
Maize	2018	[42]	7-Fungal, 1-Viral	Normalization	Improved GoogleNet Improved CIFAR10	Caffe	GTX 960	PlantVillage Google Search	2,248	612	98.9%	GoogleNet CIFAR10
Maize	2020	[43]	3-Fungal (severity) 1-Viral	–	Inception V3 Inception V4	–	–	AI Challenger	3,068	435		Inception V4
Maize	2017	[40]	1-Fungal	Lesion extraction	CNN	Keras	GTX TitanX	Field Survey	1,258	538	96.7%	–
Maize	2020	[44]	3-Fungal	RUS & ROS	VGG16 VGG19	Keras	–	Kaggle	12,326	3,082	98.2%	Mutual
Corn	2018	[32]	9-Fungal	Augmentation Contrast Enhancement Brightness Reduction Noise Reduction	GoogleNet		K620	Digipathos	80%	20%	87% (lesion)	Mutual CNNs
Cassava	2017	[45]	1-Fungal 2-Viral 2-Pest	cropping	Inception V3	Tensor Flow	–	Self collected	11,000	4,000	93%	KNN SVM
Sugarcane	2019	[47]	2-Fungal (Severity) 1-Bacterial 1-Viral 1-Abiotic	Cropping Resizing	CNN/TL	–	N/A	Self collected	10,000	3,500	95%	N/A
Radish	2017	[46]	1-Fungal	ROI selection	VGG-X	Caffe	GTX TitanX	UAV collection	1,600	400	93.3%	ML methods
Olives	2017	[48]	1-Bacterial,1-Abiotic	Segmentation Denoising	Improved LeNet	MATLAB 2016	Quadro K6000	PlantVillage	210	90	98.6%	LeNet
Soybean	2018	[49]	3-Fungal	Resizing Segmentation	LeNet	–	–	PlantVillage	70%	30%	99.32%	–
Soybean	2018	[50]	3-Fungal 2-Bacterial	Resizing Segmentation 3-Abiotic	DCNN	–	GTX TitanX	self collected	53,265	6,576	94.13% stress 90.3% severity	–
Sugar beet	2019	[51]	1-Fungal (Severity)	Resizing	Mod. Faster RCNN	Matlab 2017b	–	Self Collected	120	80	95.48%	AlexNet VGG16 Faster RCNN GoogleNet

computational effort, pre-trained networks namely VGG16, VGG19, Inception-v3, and ResNet5 were fine-tuned with the help of transfer learning. The results demonstrated that VGG16 was found to be the best by achieving just above 90% accuracy. However, for the 8-convolutional layers based CNN trained from scratch was found to be around 80% accurate on the same training and test regimes. Zhong et al. [59] proposed the use of DenseNet with multilabel classification and focused on loss entropy to classify 6 apple stress against healthy images.

Table 3 also discusses two deep learning based models to identify banana stress [60, 61]. Both use pretrained networks and use Nvidia GPUs to train networks. Some mutual comparisons were reported e.g., MobileNet-VI was found better than MobileNet on a self collected database [61].

We could find only one paper on the use of deep learning for grape plant leaf stress identification [62]. The work proposes a combination of GoogleNet and ResNet on PlantVillage dataset. The network trained using Nvidia GTX 960M parallel processing hardware was found to outperform ResNet, VGGNet and DenseNet models.

Singh et al. [24] used a multilayer CNN with 6 convolutional and 3 pooling layers to differentiate between healthy and stressed mango leaves. Further, the trained network was able to detect mango leaf (either healthy or stressed) among leaf images taken from multiple types of plants. Mango leaf data was collected by the authors their selves, however, the leaf images from other plants were taken from famous PlantVillage dataset.

6.3. Miscellaneous Leaf stress

Table 4 gives details of deep learning based techniques reported in literature for miscellaneous crops like tea, wheat, rice, walnut, coffee etc. The table also lists methods proposed for multiple plants.

This review discusses three techniques on the use of deep learning to identify leaf stress related to tea plant [64, 65, 66]. All three techniques employ pretrained convolutional neural networks on self collected images. In many cases number of training images were increased through data augmentation to fulfill the need of a deep network. Chen et al. [65] reported the use of Nvidia GeForce GTX GPU whereas in the case of the other two papers, the authors didn't reveal any information regarding any parallel processing hardware. All three methods reported more than 90% accuracy and all three were found to outperform conventional machine learning based models like SVM, KNN and Bayesian classifiers etc. Wheat crop stress have been rarely addressed in the literature before 2017. We collected three recent works addressing wheat crop leaf stress with deep learning approaches. A unique work on the use of deep convolutional network using mobile capture devices was presented by [37]. The architecture used a modified ResNet-50 with 14 layers. The novelty of this technique is the use of a mobile device to run a lightweight deep network for real-time monitoring. However, the research work addressed only three fungal stress of the wheat plant. A more recent work [67] addresses the problem using a specialized matrix convolutions based CNN along with Nvidia GTS 1080 GPU. Experiments were conducted on their collected dataset having more than $83,000$ images split in to 70%, 30% for the purpose of training and testing. The technique produced the maximum efficiency equal to 96.5% and was found better than AlexNet and VGG16 deep networks.

Further, eleven different stress of rice were identified using a deep CNN by [68]. The dataset used contained more than 10,000 patches obtained from 500 field images. The deep network was found to be more accurate compared to SVM and Particle Swarm Optimization (PSO), etc.

Table 4 also provides details of techniques addressing plant stress of more than one plants.Hang et al.,[69] proposes an improved version of VGG16 to address 10 different stress from three plants namely apple, cherry and corn. Their network was trained on AI challenger dataset using Nvidia GTX 1080Ti GPU and was found better than many pretrained deep networks including AlexNet, GoogleNet, VGG16, VGG19 and ResNet5 etc.

Table 3: Summary of deep learning techniques surveyed for fruits leaf stress.

Plant	Year	Ref.	Stresses	Preprocessing	Network	Software	GPU	Dataset	Training	Testing	Accuracy	Comparisons
Cucumber	2019	[52]	4-Fungal 2-Bacterial	Cropping Lesion Extraction	Modified AlexNet	TensorFlow	GTX 1080Ti	Self collected	80%	20%	98.9%	DCNN AlexNet
Cucumber	2019	[53]	4-Fungal	Augmentation Resizing	3-Channel CNN	Matlab 2017	–	Self collected	Variable	Variable	91.16%± 2.16	SRC IPT GLSVD SVM
Tomato	2018	[54]	3-Fungal 1-Bacterial 1-Viral	Resizing	CNN	–	–	PlantVillage	6,300	2,700	99.84% Color 95.54% Grayscale	–
Tomato	2017	[55]	4-Fungal 1-Bacterial 2-Pests 2-Abiotic	Annotation Augmentation	Faster RCNN VGG16 Resnet-X	VOC challenge	GTX TitanX	Self collected	4,000	1,000	86%	Mutual
Tomato	2018	[57]	3-Fungal 2-Viral 1-Pest	Segmentation Augmentation	AlexNet VGG16	Matlab 2017b	Yes	PlantVillage	Variable	Variable	97.26% AlexNet 97.49% VGG16	ML methods
Tomato	2020	[56]	3-Fungal	Augmentation	Attention Residual CNNs Residual CNN	Tensorflow	Tesla P100	PlantVillage	70%	30%	98%	CNN
Apple	2018	[58]	2-Fungal 1-Viral	Denoising	Modified AlexNet	Caffe	Tesla P100	Self collected	10,888	2,801	97.2%	SVM, AlexNet VGG16, GoogleNet Resnet-20
Apple	2020	[59]	3-Fungal (Severity)	Resizing	DenseNet 121	–	–	AI Challenger	1,600	400	93.51%	
Apple	2019	[63]	4-Fungal	Annotation Augmentation	VGGNet	Caffe	GTS 1080Ti	Self collected	19,773	6,604		Faster R-CNN SSD DSSD & R-SSD
Apple	2017	[29]	1-Fungal (Severity)	Normalization Augmentation	VGG16	Keras	GTX TitanX	PlantVillage	Variable	Variable	90.4%	VGG19, Inception-V3 ResNet5
Banana	2017	[60]	2-Fungal	Resizing	LeNet	–	–	PlantVillage	3,000 Variable	700 Variable	98.6%	–
Banana	2019	[61]	3-Fungal, 1-Bacterial 1-Viral, 1-Pest, 1-Abiotic	Annotation	ResNet-50 MobileNet-V1	TensorFlow	Tesla M60	Self collected	21,000	9,000	99%	MobileNet
Grape	2019	[62]	3-Fungal	Resizing	GoogleNet+ResNet	Keras	GTX 960M	PlantVillage	960	419	98.57%	ResNet, VGGNet DenseNet
Mango	2019	[24]	1-Fungal, 2-Others	Normalization Enhancement Scaling	AlexNet	TensorFlow	GT 710	PlantVillage Self collected	1,760	440	97.3%	PSO SVM, RBFNN MCNN

Kamal et al. [70] used separable CNN models to reduce number of parameters and achieved accuracy comparable to many other deep learning models on various plant leaves. MobileNet used by these authors achieved 98.65% accuracy with fewer parameters than VGGNet. Their dataset contained both clean images and with altered backgrounds.

Another similar work by [71] uses a nine layers deep convolutional neural network to classify 38 stress from 14 plants with the help of Nvidia DGX-V100 GPU. The recognition accuracy was compared with conventional machine learning based models.

Another noteworthy work was presented by [72] where 58 stress from 15 different plants were identified using four different pretrained deep learning models namely AlexNet, AlexNet-OWTB, GoogleNet and VGGNet. The network was trained on PlantVillage database using Nvidia GTS 1080Ti GPU and the results produced by different deep networks were compared with each other. The work by [25] uses variable amount of training and test data from 20% to 80% on PlantVillage dataset and the mutual recognition accuracy values were compared.

Some authors have used the lesion or spot of stressed part instead of using the whole leaf [73]. This approach is useful when a leaf is infected of multiple stress. Another recent work [38] on coffee leaf stress has proposed a similar lesion extraction methodology. The authors trained a deep network on two types of data sets i.e., one comprising of stressed leaf and the other containing portions showing lesions. Performance of the network was analyzed using both datasets. Screenshots of a few infected tea leaves are shown in Fig. 10.

Authors in [14] have compared performance of different pretrained convolutional neural networks on data taken from PlantVillage dataset. Their aim was to select the model having minimum training cost (i.e., time) and provides maximum classification accuracy on their selected set of images. DenseNet 121 deep network fulfilled both criteria by obtaining around 98% accuracy and by being the fastest compared to VGG16, Inception V4 and ResNet 50 networks.

7. Discussions and Conclusion

Inspite of dozens of recent deep learning based efforts to identify plant leaf stresses, there are still some open challenges like the use of real world data, automatic background elimination and the use of handheld devices to train and test complex convolutional neural networks with millions of parameters. A large body of the published research fine tuned pretrained networks like GoogleNet, VGGNet or AlexNet etc. on their training data. This survey has demonstrated that these transfer learning based methods have produced better recognition accuracy compared to the case where the network is trained from scratch. Most of the research work has been built around a publicly available dataset namely PlantVillage. It contains more than $50,000$ images sufficient to train any convolutional neural network. Some authors used less than one thousand original images e.g. [62, 24, 64] but data augmentation has been their mainstay to obtain ample number of images sufficient to train a deep model.

Almost all the authors have used augmentation techniques [80, 81] to artificially expand the dataset to improve its performance ability. Some basic augmentation steps involve rotation, cropping, adding noise, and grayscale conversion. A few such examples taken from published works are shown in Fig. 11.

Recently proposed deep networks in this area have produced great recognition accuracy for almost all types of plants (generally above 90%). Conventional machine learning based feature extraction and classification constitute a major class of techniques against which all deep networks surveyed for this work have produced better results. A large set of techniques in this paper also compare performance of their proposed deep network against other commonly used networks like GoogleNet, AlexNet, Inception-X etc.

Table 4: Summary of deep learning techniques surveyed for miscellaneous plants leaf stress.

Plant(s)	Year	Ref.	Stresses	Preprocessing	Network	Software	GPU	Dataset	Training	Testing	Accuracy	Comparisons
Tea	2019	[64]	3-Fungal	Denoising	CIFAR10	–	–	Self collected	312	40	92.5%	SVM, KNN Bayes, BP-NN
Tea	2019	[65]	6-Fungal, 1-Algal	Resizing	LeafNet	Matlab	GeForce GTX	Self collected	6,325	788	90.16%	SVM, MLP
Tea	2019	[66]	3-Fungal	Segmentation Augmentation	VGG16	–	–	Self collected	70%	30%	90%	SVM, Mutual
Wheat	2019	[37]	3-Fungal	Cropping Resizing Normalization	Mod. ResNet	Tensorflow	–	W-2014	80%	20%	83.4%	ResNet50
Wheat	2017	[74]	5-Fungal, 1-Bacterial	Segmentation	VGG-FCN-VD16 VGG-FCN-S	Python	GTX 1080	WDD-2017	7,384	1,846	97.95% FCN-VD16 95.12% FCN-S	Conventional CNN
Wheat	2019	[67]	4-Fungal, 2-Bacterial, 1-Abiotic	Augmentation	Mb-CNN, Matrix convol.	Tensorflow	GTX1080	Self collected	58,282	24,978	96.5%	AlexNet, VGG16
Rice	2017	[68]	7-Fungal, 3-Bacterial	Normalization PCA Whitening	CNN	Matlab 2012a		Pest Dataset Self collected	90%	10%	95.48%	SVM, BP, PSO
Ginkgo tree	2020	[75]	1-Fungal (Severity)	Resizing Augmentation	VGG16, Inception V3	Tensorflow	–	Self collected	12,000	3,000	98.44% Lab images 92.14% Field images	Inception V3
Walnut	2020	[76]	1-Fungal	Segmentation Color Spaces	CNN	Keras	GTX 1080Ti	Self collected	3,500	1,000	98.7%	Inception V3, VGG16, ResNet50, DenseNet
Coffee	2020	[38]	3-Fungal, 1-Moth (Severity)	Cropping	ResNet50	PyTorch	GTX1060	Self collected	80%	20%	95.24% Biotic stress 86.51% Severity	AlexNet, GoogleNet VGG16, MobileNet
Multiple	2019	[70]	–	Resizing	Modified MobileNet	–	–	PlantVillage	70%	30%	98.34%	VGG, AlexNet, Mutual
Multiple	2019	[69]	4-Fungal (Severity)	Resizing Augmentation	Improved VGG16	Caffe	GTX 1080Ti	AI Challenger	5,588	520	91.7%	AlexNet, GoogleNet, VGG16, VGG19, Inception V3, ResNet
Multiple (14)	2019	[71]	17-Fungal, 4-Bacterial, 2-Viral, 2-Oomycetes, 1-Pest	Augmentation	9 Layers CNN	Python	DGX-1 V100	PlantVillage	55,636	5,000	96.46%	SVM, Decision Tree, Log. Regression, KNN
Multiple (3)	2019	[77]	–	Augmentation	CNN encoder	Python	–	PlantVillage	67%	33%	97.50%	ML methods
Multiple (15)	2018	[72]	30-Fungal,3-Viral,3-Bacterial	Resizing Cropping	AlexNet AlexNet-OWTB GoogleNet VGG	Torch7	GTS 1080	PlantVillage Self collected	70,300	17,548	99.53%	Mutual
Multiple (4)	2019	[78]	3-Fungal, 3-Pests, 2-Bacterial	Resizing	AlexNet, SqueezeNet, GoogleNet, VGGNet ResNetX, InceptionV3	Matlab	Quadro M4000	Self collected	1,800	200	97.86%	Mutual
Multiple (5)	2016	[79]	11-Fungal, 2-Bacterial, 1-Pest	Resizing Augmentation	CaffeNet	Open CV & Python	TitanX	Internet	30,880	2,589	96.3%	Mutual
Multiple (12)	2016	[25]	17-Fungal, 4-Bacterial, 2-Viral, 2-Oomycetes, 1-Mite	Segmentation	AlexNet GoogleNet	–	–	PlantVillage	Variable	Variable	99.35%	Mutual
Multiple (14)	2019	[14]	–	Normalization	VGG16, InceptionV4, ResNet50, 101,152, DenseNet 121	Keras (Theano)	Tesla K40	PlantVillage	80%	20%	99.75% 97.5%	Mutual Mutual

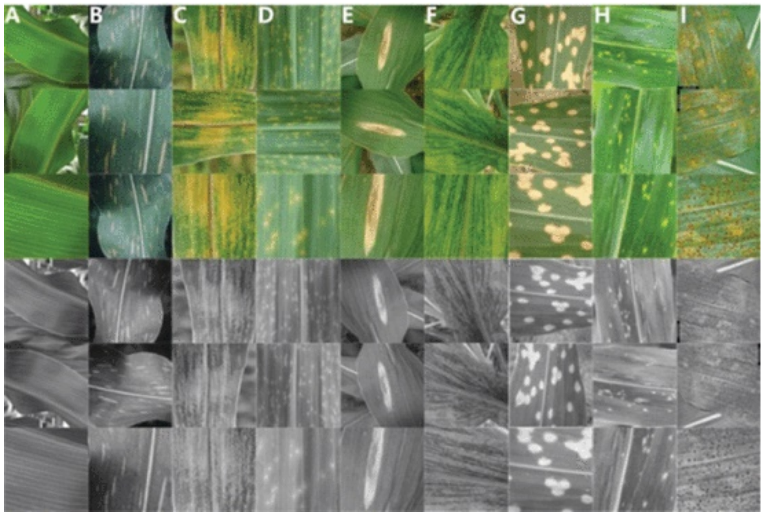


Figure 11: Augmentation applied on maize leaf images by [42]

While most of the research addresses different types of leaf stresses, some papers take severity of stress as classes [47, 51, 82]. Early detection of stress severity makes precise treatment of the stress possible. An example of a healthy leaf along with three increasingly severity levels of stress are shown in Fig. 12. The images were taken from the work presented by [29] on use of deep learning to identify severity level of plant stress. Another deep learning based technique uses three severity levels for leaf stress related to Ginkgo tree [75]. Authors in [38] classify different biotic stresses along with severity levels and compared their results with existing machine learning based methods. However, stress stage identification along with its various types is still an open issue because a leaf infected by multiple stresses can mislead the deep network trained on severity levels.

Figure 13 shows each plant versus number of times it was handled by a deep learning based approach reviewed for this work. It can be seen that the maize/corn is the highly cited crop in deep learning based literature addressing plant leaf stress. Fruits like apple, tomato, cherry and orange etc. have also been the focus of deep learning based approaches in this field.

It was also observed that some deep learning based network models have been used more than others in recent research contributions on plant leaf stress recognition. Figure 14 shows that VGG16 is the top network being employed in latest literature on leaf stress identification of various fruits and vegetables etc. Further, VGG16 and VGG19 have also been widely used as networks with which several modified deep networks have been compared for various plants [67, 29]. After this, Resnet50, Alexnet and Google Net are equally famous and have also been the focus in the last five years.

The comparisons shown in Tables 2, 3 and 4 can be used to deduce that the classification accuracy on almost all kinds of plant leaf stress is much higher using deep networks of various kinds compared to the conventional machine learning methods. However, there are still some research gaps that need to be addressed in future. A brief summary of some open research questions in the field is given as under:

7.1. Challenges

Following are some challenges faced by researchers applying deep learning techniques for plant leaf stress recognition:

1. Unavailability of large datasets has been a great hurdle on the use of deep learning methods in the field of plant leaf stress recognition. Fortunately, a large datasbase containing thousands of images namely PlantVillage is now available [33]. However, the availability of datasets containing real field images is still missing.

(a) Healthy leaf

(b) Early stage of stress

(c) Middle stage of stress

(d) Last stage of stress

Figure 12: Apple stress severity dataset [29]

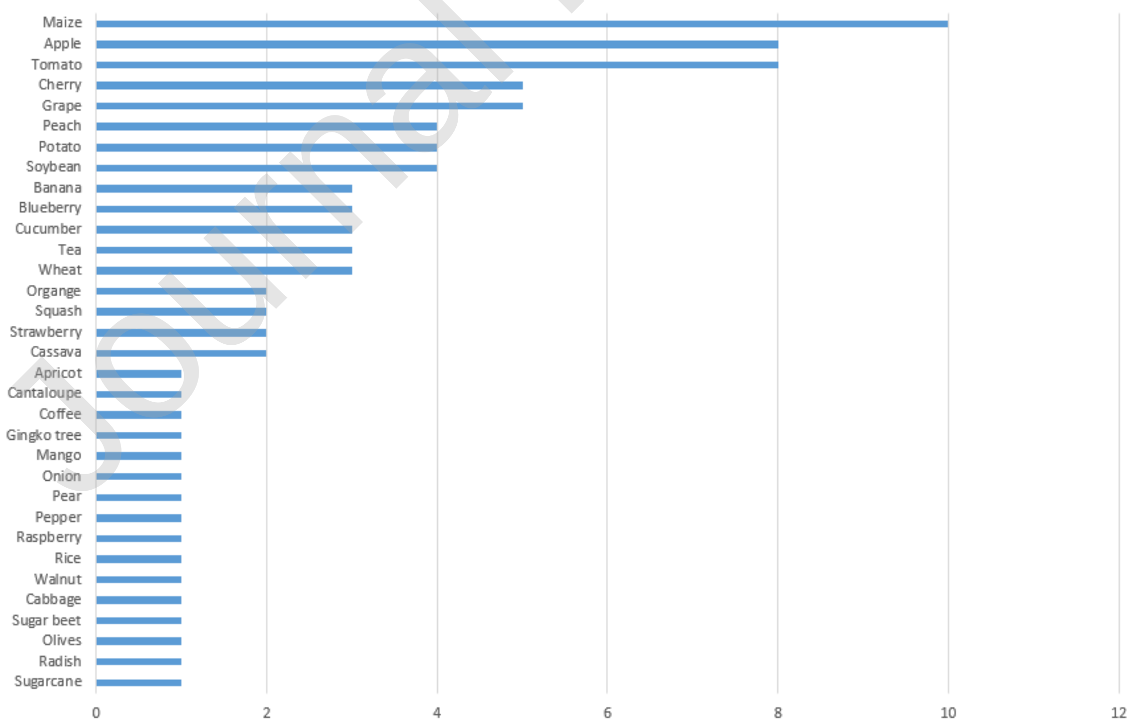


Figure 13: Histogram of plants addressed by the research works included in this review.

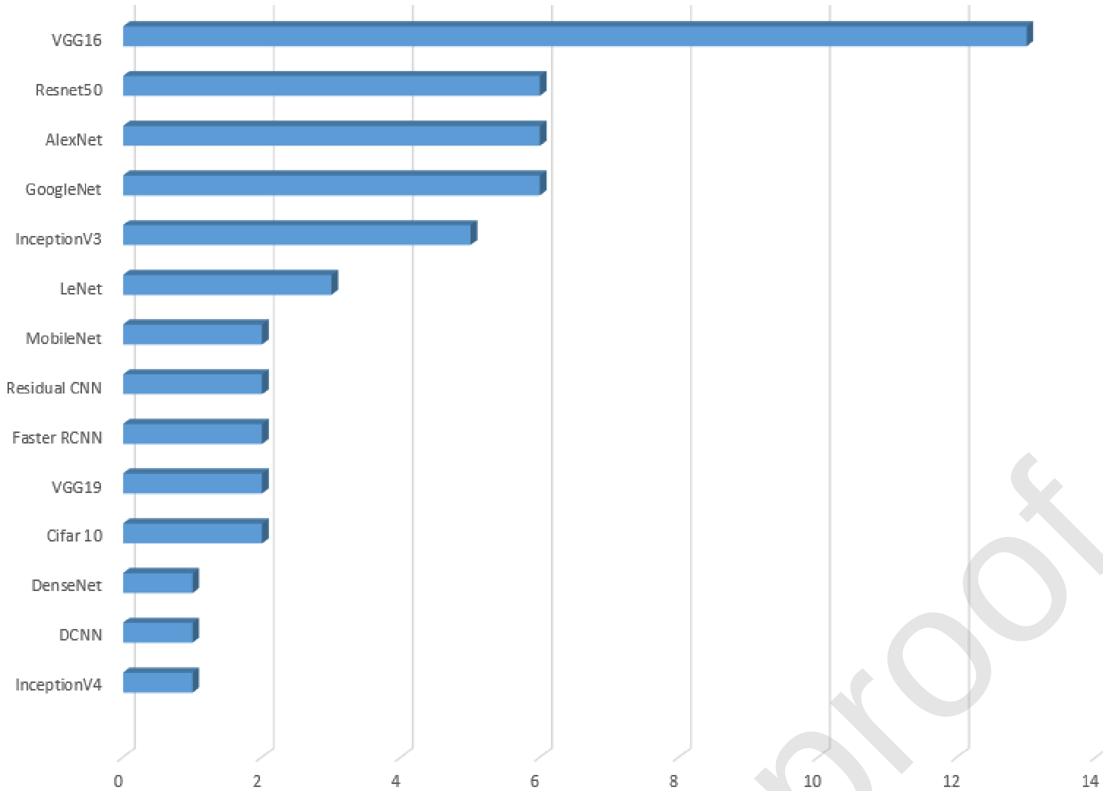


Figure 14: Histogram of deep network models used for plant leaf stress identification

2. Images from real world scenarios is another research gap as most of the authors [25, 77, 29, 71] have used synthetic images from publicly available datasets which contain cropped and pre-segmented images only. Some authors did use image sets from cluttered background but on their self collected small datasets after some necessary preprocessing [70]. Authors in [75] compared performance of their proposed deep learning methods on field and lab images keeping in view the fact that different illumination, lightning conditions, capture angle and distance vary the results of deep networks/classification accuracy values for different plant may vary on the same network [72]. Almost all others have performed necessary preprocessing steps in self collected field images to increase recognition accuracy.
3. Annotating self collected data with the help of a field expert is another issue faced by deep learning researchers from computer science background.
4. Detecting early onset of plant diseases is an important aspect in this area of research. Detecting a plant being infected at an early stage enables farmers to take corrective measures at lower cost. Hyperspectral imagining has been used for this purpose but the area captured on ground using thermal sensors and light reflector sensor [83] is very large which makes detection of a disease or infected area a challenge.
5. All published work studied for the sake of this review propose deep networks specific to a certain plant. The classification accuracy is not guaranteed to remain the same as the host-network pair changes. Coming up with a universal CNN model whose performance is independent of plants and/or stress(es) is another open challenge.

7.2. Research Gaps

Based on the research papers reviewed for this survey, following are some future directions for newly entered researchers in this field:

1. A lot of work on deep networks has focused on biotic stresses but practically both abiotic and biotic stresses can co-exist

on a vulnerable host (plant). Though authors in [61] and [48] have covered both biotic and abiotic stresses but there is still a lot of room in this area.

2. A leaf can be affected by more than one stresses at a time. The host becomes more vulnerable to a pathogen if it is already deficient in nutrition or another abiotic stress preexists. This co-existence of multiple stresses is very common in reality but unfortunately has yet been given a lesser attention. The available literature rarely talks about this issue except some authors have discussed manual lesion extraction. Hence, this can be aimed as another future research direction.
3. Performance of some deep learning networks may vary for different crops [73]. Authors discussing several plants have thereby mentioned performance of their proposed network on different crops separately and some have done otherwise [31] Searching for a universal deep network providing large recognition accuracy on a set of crops is another future direction.
4. Several researchers have used hyperspectral [84, 85], thermal and multispectral imaging for agricultural applications including but not limited to recognizing plant leaf stress [86, 87]. Presently the use of hyperspectral imaging is showing promising results to detect stress type, health status, infestation of pest, mites & weeds and contaminants [88] but with the help of conventional machine learning models. Since, the scope of our research is limited to deep learning only, most such papers were dropped for this review. However, it is widely known today that convolutional neural networks provide a new direction for all types of image processing based applications, these networks can be used in future for hyperspectral crop images especially to detect early onset of stress(s) [89, 90]
5. With continuously improving deep learning models, an identified challenge for researchers is to look for optimal parameters [91] and layers to achieve convergence. Different conventional optimization algorithms perform poorly on high dimensional data [92]. The problems associated with already trained network and use of ensemble learning technique to achieve optimal parameters as discussed by [44, 93] can be another future work.
6. Life cycle of different stress types pertaining to a single plant differ with each other. We are in dire need of deep learning models that detect and classify all stages/severity levels of a stress so that contagious diseases can be detected and cured at an earlier stage [94].

This paper can be seen as a major attempt to provide an up-to-date overview of the research work carried in this all important field of agriculture.

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Appendix A. Abbreviations

Various abbreviations used throughout this paper are given in Table A.1.

Table A.1: A summary of abbreviations used in this paper.

Abbreviations	Explanation
API	Application Programming Interface
BP	Back propagation
CIFAR	Canadian Institute for Advanded Research
CNN	Convolutional Neural Network
DCNN	Depp Convolutional Neural Network
DSSD	Deconvolutional Single Shot Detector
FC	Fully Connected
FCN	Fully Convolutional Network
GLSVD	Global and Local Singular Value Decomposition
GPU	Graphical Processing Unit
GTX	GeForce eXtreme
IPT	Iamge Processing Technique
KNN	K-Nearest Neighbor
MCNN	Mobile-Nets Convolutional Neural Network
ML	Machine Learning
MLP	Multi Layer Perceptron
NLB	Northern Leaf Blight
PSO	Particle Swarm Optimization
RBFNN	Radial Basis Function Neural Network
RCNN	Region-Based Convolutional Neural Network
ReLU	Rectified Linear Unit
ResNet	Residual Neural Network
RoI	Region of Interest
ROS	Random OverSampling
R-SSD	Rainbow Concatenated Single Shot Detector
RUS	Random UnderSampling
SRC	Sparse Representation based Classification
SSD	Single Shot multi-box Detector
SVM	Support Vector Machine
TL	Transfer Learning
UAV	Unmanned Air Vehicle
VOC	Virtual Object Classes
VGG	Visual Geometry Group
WDD	Wheat Disease Database