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Plant Disease Severity Assessment Based on Machine Learning and Deep Learning: A Survey

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Abstract

The world's agricultural production suffers huge losses estimated between 20% and 40% annually. 40% to 50% of such losses are due to pest and diseases which cause significant economic losses every year. Precise assessment of severity is crucial for suitable management of crop diseases. It helps famers to avoid yield losses, reduce production costs, ensure good disease management and so on. This paper is a review of plant diseases severity estimation solutions proposed by researchers the last few years and based on Image Processing Techniques (IPT), classical Machine Learning (ML) and Deep Learning (DL) algorithms. The analysis of these solutions has allowed us to identify their limitations and potential challenges in plant disease severity assessment.

Keywords

Plant, Disease, Severity, Machine Learning, Deep Learning

1. Introduction

The world's agricultural production suffers huge losses estimated between 20% and 40% every year [1] [2]. 40% to 50% of such losses are due to pest and diseases [3] [4]. These losses are both quantitative and qualitative and as a result, they are responsible for significant economic losses annually and affect the Gross Domestic Product (GDP) of countries. Plant pest and disease protection has become an important research area, due to its highly correlation with food security, climate change and environmental sustainability. It is an essential tool for precision agriculture.

However, knowledge of the disease severity is an essential factor in crop disease protection and management [4] [5]. Crop disease severity is the ratio of plant units with visible disease symptoms to the total plant unit (e.g. fruit, leaf) [6]. Diagnosis of crop disease and disease severity estimation are closely related. It is therefore essential to identify the disease severity stage as early as possible in order to remedy the yied loss. Traditional methods for disease severity estimatimation mostly rely on manual labor, which is labor-intensive, slow and highly subjective [7] [8] [9]. It requires plant protection experts to visit the field to identify the disease and determine its severity.

In recent years, thanks to advances in computer imaging technology and improved hardware performance, computer vision and artificial intelligence have been widely used in agriculture for plant species classification, disease identification and plant disease severity assessment [10]. Solutions proposed by researchers the last few years for disease severity estimation are based on images processing techniques (IPT), classical Machine Learning (ML) and Deep Learning (DL) algorithms [1] [7] [8].

This paper is a review of plant disease severity assessment solutions proposed by researchers the last few years. The specific contributions of this paper include:

- Advantages of plant disease severity assessment.
- Analysis of proposed crop diseases severity estimation solutions based on IPT, ML or DL.
- Limitations of proposed solutions and potential challenges.

The paper is organized as follows: Section 2 identifies the advantages of plant disease severity assessment in agriculture, Sections 3 provides a critical analysis of the proposed solutions based on IPT, classical ML and DL algorithms, Section 4 shows the potential challenges in crop disease severity estimation and the last Section concludes the paper.

2. Advantages of Plant Disease Severity Assessment

In a field, a disease can spread rapidly over the entire crop batch and cause a field-wide epidemic, which is undoubtedly devastating. In order to effectively monitor and control such situations, it is important to specify earlier not only the type of disease, but also its severity, which is the ratio between the plant unit showing visible symptoms of the disease and the total plant unit [6]. For example, the ratio of diseased area to leaf area (see **Figure 1** and **Figure 2**). This is why the precise quantification of crop diseases is an absolute necessity in agriculture. Thus, asssessing disease severity enables growers to rationalize disease control, for example by deciding on the right dose of fungicide and type of pesticide, as well as the time of day to spray [8] [11]. A reliable and accurate estimation of disease severity enables farmers to predict epidemics in their fields and yield losses, and to assess disease resistance in crop germplasm [12] [13] [14]. It can also help farmers with pesticide management, disease forecasting, spatio-temporal epidemic modeling and crop loss modeling [7] [15] [16]. Pesticide management plays an important role in protecting the environment by simultaneously reducing crop, soil and water pollution and avoiding pesticide residues in fruits

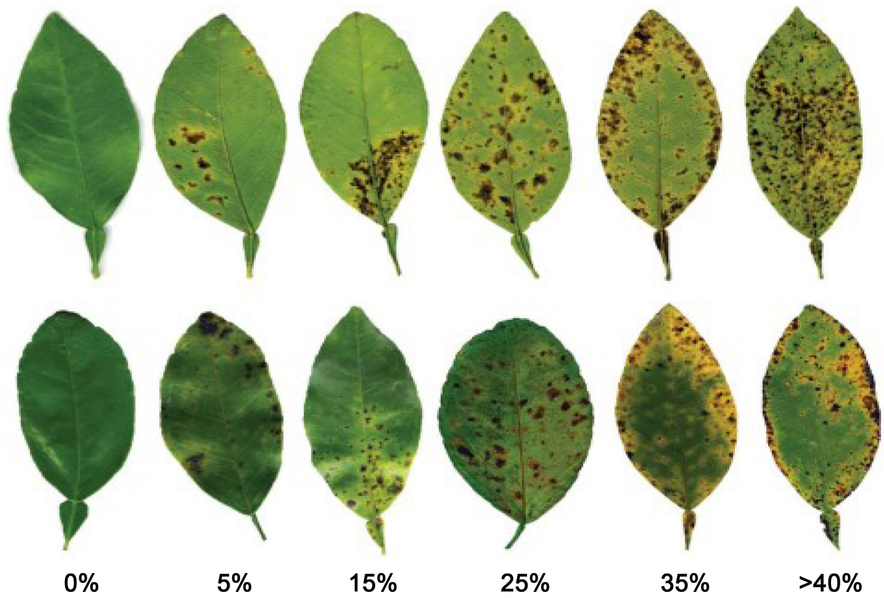

Figure 1. Visual scale of greasy spot severity in grape fruit leaves [17].

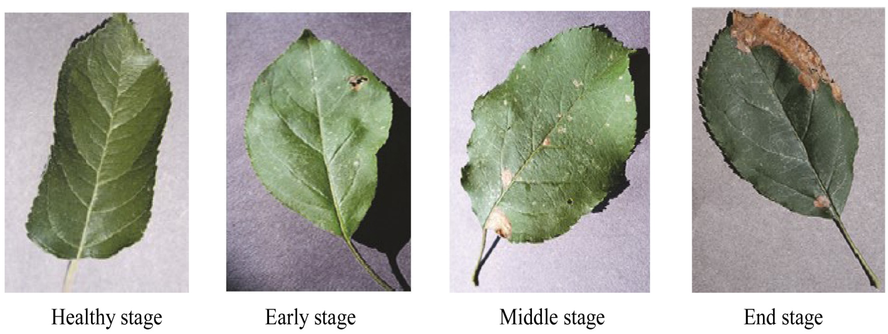

Figure 2. Leaf images of four severity stages (healthy, early, middle and end) of apple black rot disease [18].

[8] [19]. Early disease severity estimation is essential in global food security [18].

However, traditionally, disease severity is determined manually by experts by estimating the visual surface area of lesions on plants (e.g. leaf, fruit, etc.). This process is slow, time-consuming, highly subjective and largely dependent on the level of experience of agronomists and farmers for visual scoring [1] [7] [20] [21]. Incorrect assessment of disease severity in plants can lead to erroneous conclusions, resulting in wasteful or inefficient use of pesticides, which can further exacerbate losses [15] [22] [23] [24].

3. Automatic Disease Severity Assessment

In the literature, several solutions have been proposed for estimating the severity of plant diseases. These solutions can be divided into three types:

- Visual assessment, traditionally used by plant experts,
- Solutions based on hyperspectral imaging (image processing techniques) or

ML,

- And more recently, solutions based on DL.

For the purposes of this paper, we worked on 47 articles whose work focused on estimating the severity of plant diseases. The articles were searched on Google Scholar, Springer Link, Web of Science, IEEE Xplore, Scientific Research, Frontiers, etc., using the keywords "disease-severity-assessment-plant". **Figure 3** shows the number of studies carried out on this topic every year, between 2008 and 2023.

These work concerns different crops, different diseases and different approaches for determining disease severity. Among the crops covered by the 47 reviewed articles, tomato and maize are the most treated (8 times). It is followed by tomato (8 times), wheat (5 times) and strawberry (4 times) (see **Figure 4**).

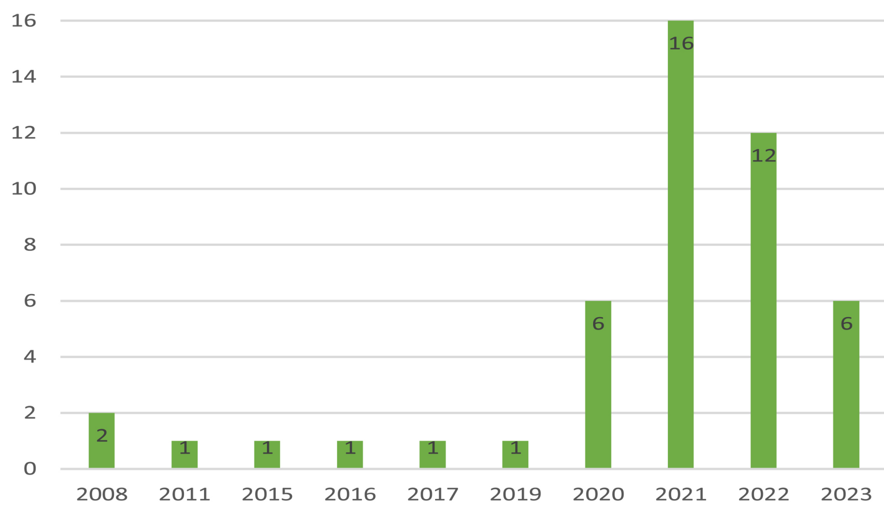

Figure 3. Graph showing the distribution of publication years for 47 articles based on the keywords "disease-severity-assessment-plant" from Google Scholar, Springer Link, Web of Science, IEEE Xplore, Scientific Research, etc.

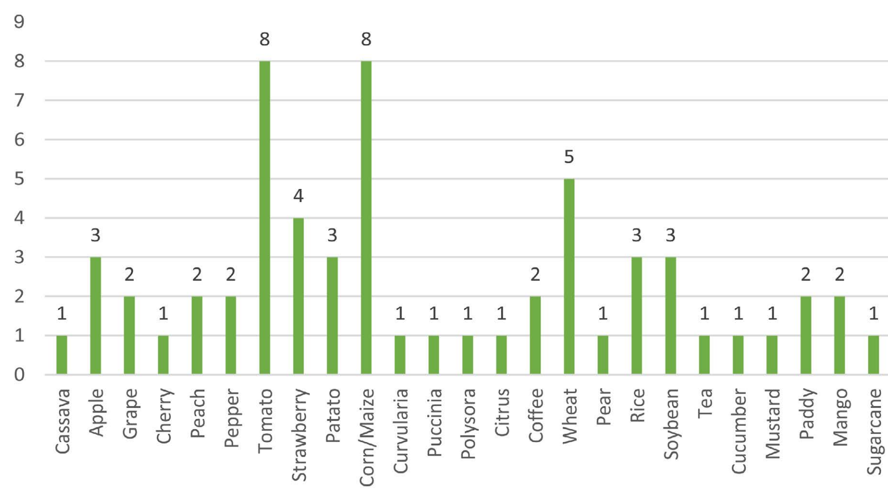

Figure 4. Graph showing the number of times crops were treated in the 47 reviewed papers.

The definition of the severity grades or lavels is essential in diseases severity estimation. Based on the 47 reviewed articles, we can say there are three categories of severity grades namely qualitative grade, quantitative grade and direct calculation of the percentage of the disease lesions (see **Figure 5**). For example, [18] used Healthy, Early, Middle and End severity levels which are qualitatives. [25] used healthy (<0.1%), very low (0.1% - 5%), low (5.1% - 10%), high (10.1% - 15%) and very high (>15%) grades which are quantitatives. In [26], the percentage of the disease lesions is directly calculated. In the following subsections, we take a closer look at solutions based on IPT and ML and DL algorithms.

3.1. Solutions Based on IPT

In agricultural research, IP technology has undergone significant development. Solutions based essentially on IP technology have been proposed by reseachers for assessing plant leaf disease severity. For instance, Wijekoon *et al.* [27] used multispectral images thresholding operation to calculate the ratio of infected area, lesion color index and severity index of soybean leaf infected by rust disease. Weizhong *et al.* used the Sobel operator to segment soybean rust disease and to determine the spot edge and disease severity of the plant, which is measured by calculating the quotient of disease spot area and leaf area [28]. In [29], authors applied simple threshold and triangle thresholding methods to respectively segment the diseased leaf area and lesion region on the leaf. The results show an accuracy of 98.60% for estimating the severity of brown spot on soybean leaves. Thus IP technology to measure crop disease severity is convenient and accurate but the severity of the disease measured is depends upon segmentation of the image. Authors of [30] developed a mobile application based on image processing. This app is able to calculate the severity percentage of six different diseases with typical lesions of varying severity. Palma *et al.* proposed an approach for automatic quantitative assessment of disease severity based on leaf images, regardless of disease type. The proposed method is based on a highly

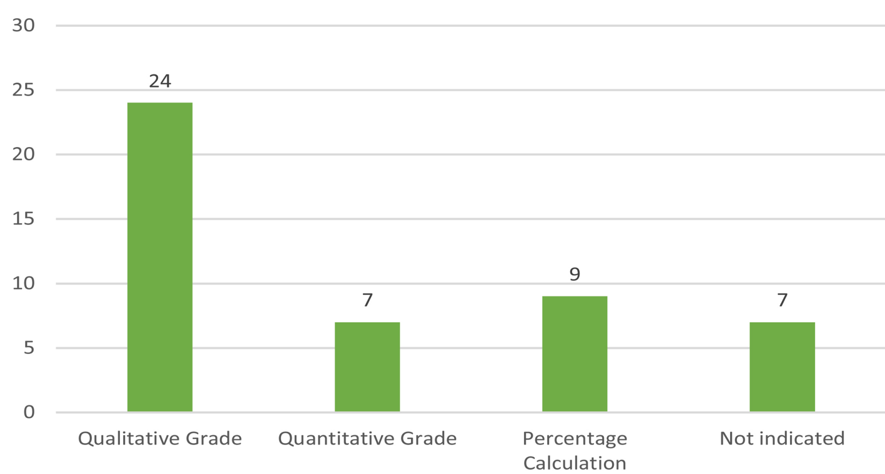

Figure 5. Graph showing the number of times categories of grades are used in the 47 reviewed papers.

efficient, noise-free positive nonlinear dynamic system that recursively transforms the image of the leaf until only the symptomatic patterns of the disease remain [31].

3.2. Solutions Based on ML

In the literature, there are very few works based on classical ML algorithms for estimating crop disease severity. ML-based solutions often use IPT. IPT are used to improve the quality of the images used, while ML algorithms are used for image segmentation, feature extraction and image classification. For example, Owomugisha *et al.* [32] used image processing technics and classical ML algorithms such as linear SVC, KNN and Extra Trees to classify four cassava diseases (mosaic, brown streak, bacterial blight and green mite) and assess their severity on diseased leaves. They used a dataset of 7386 images divided into 5 severity levels ranged from 1 to 5. They obtained accuracy scores of 99%. Authors of [33] utilized ML models to detect and classify downy mildew (DM) disease severity in watermelon in five disease severity stages namely low, medium, high and very high. They used Hyperspectral watermelon leave images collected in laboratory and in the field by a UAV and implemented multilayer perceptron (MLP) and decision tree (DT). Results show that classification accuracy increased when the disease severity increased and the best classification results were obtained from the MLP method in high and very high severity stages (87% - 90%). Jiang *et al.* [34] used two unsupervised learning algorithms namely K-means clustering and spectral clustering and three supervised learning algorithms including SVM, RF, and KNN to assess the severity of wheat leaf stripe rust disease. They used a dataset of 400 samples splitted into height severity levels namely 1%, 5%, 10%, 20%, 40%, 60%, 80%, and 100%. RF model obtained the best assessment performance with an overall accuracy of 100%. **Table 1** summarizes the abovementioned works according to the year of publication, the crop concerned, the parts of the crop infected, the diseases treated, the disease severity grades, source of the dataset and the algorithms used.

3.3. Solutions Based on DL

Based on the 47 articles we worked on, the majority of solutions proposed for estimating plant disease severity are based on DL and essentially on Convolutional Neural Networks (CNNs). DL-based solutions can be divided into two categories: CNN-based solutions and CNN-based segmentation networks. These solutions generally follow the workflow described in **Figure 6**.

3.3.1. CNN-Based Solutions

During the last decade, several solutions based on CNN have been proposed in the filed of crop diseases diagnosis. The estimation of disease severity, an extension of disease diagnosis, is also an area in which several CNN-based solutions have been proposed in recent years. For instance, automatic disease severity assessement of plant based on CNN was first proposed in 2017 by Wang *et al.* [18].

Table 1. Summary of solutions based on ML.

Article	*Year*	*Crop*	*Part*	*Diseases*	*Severity Grade/ Level*	*Dataset*	*Models used*	*Results*
[32]	2016	Cassava	Leaf	Cassava mosaic, Cassava brown streak, Cassava bacterial blight, Cassava green mite	5 severity levels ranged from 1 to 5	Self-collected (7.386 images)	SVC, KNN and Extra Trees	Accuracy scores close to 99%.
[33]	2022	Watermelon	Leaf	Downy mildew	Low, medium 1, medium 2, high and very high	Self-collected	MLP and DT	Best performance: 87% - 90% of accuracy
[34]	2023	Wheat	Leaf	Stripe rust	1%, 5%, 10%, 20%, 40%, 60%, 80%, and 100%	Self-collected (400 images)	K-Means, Spectral clustering, SVM, RF and KNN	KNN: 100% of overall accuracy

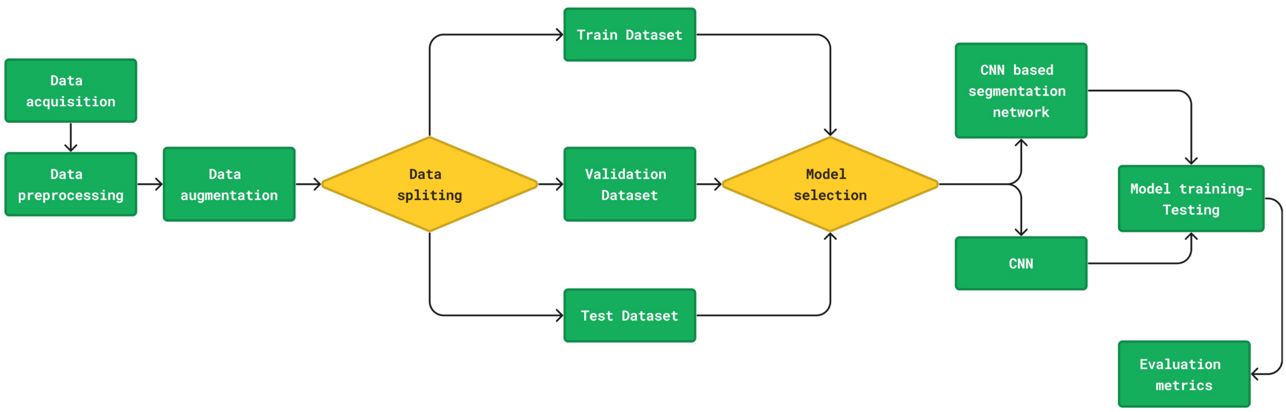

Figure 6. CNN-based solutions general flowchart.

Similarly, several authors have proposed plant disease severity assessment solutions based on well-known CNN such as VGG16, VGG19, ResNet18, ResNet50, ResNet101, Inception-V3, GoogLeNet, AlexNet, SqueezeNet, DenseNet121, MobileNetV2, NASNetMobile [4] [5] [12] [14] [15] [18] [24]. Some authors have proposed their own CNNs, which have given better results than well-known CNNs [11] [21] [23] [35]-[41]. Some solutions are based on the combination of CNN and classical ML algorithms such as Random Forest [19] and SVM [13]. Among these CNN-based solutions, several have used the principle of Multi-task learning [1] [4] [8] [10] [14] [25] [35] [37] [42]. Multi-task learning, as opposed to single-task learning, is a learning principle in which several linked tasks can be learned simultaneously [1]. Plant disease classification and disease severity estimation are two related tasks, which can be learned simultaneously using multi-task learning. Multi-task learning is more advantageous than Single-task learning because it can reduce the risk of overfitting and lead to better generalization of a model [43].

These CNN-based solutions have achieved extraordinary performances ranging from 70% to 99% accuracy.

Table 2 is a summarize of theses above-mentioned works according to the year of publication, type of architecture (single or multi task), crop concerned, parts of the crop infected, diseases treated, the disease severity grades, source of the dataset, models used and results obtained.

3.3.2. CNN-Based Segmentation Networks Solutions

CNN-based segmentation is widely used in object detection and localization. CNN-based segmentation networks have also been used to assess the severity of plant diseases and other related agricultural tasks. Of the 47 articles reviewed, seven used a CNN-based segmentation network, such as Unet [10] [12], Mask R-CNN [49] [50] [51], Faster R-CNN [8] [42], SegNet [26], DeepLav [26] and so on. They are based on segmentation of infected areas (of the leaf, fruit, etc.) to quantify disease severity (see **Figure 7**). For crop disease severity assessment. Su *et al.* [49] proposed a solution based on Mask-RCNN for the detection and severity estimation of Fusarium Head Blight (FHB) on wheat spikes. Authors defined fifteen severity grades (from grade 0 to grade 14). The proposed solution achieved accuracies of 77.76% and 98.81%, respectively for FHB detection and severity assessment. Chen *et al.* [20] developped a Deep Learning algorithm (BLSNet) based on Unet for rice leaf bacterial lesion segmentation and severity estimation. Goncalves *et al.* [26] used six CNNs namely Unet, SegNet, PSPNet, FPN, DeepLabV3 (Xception) and DeepLabV3 (MobileNetV2) to estimate the severity of Coffee leaf miner, soybean rust and wheat. They used a dataset for each of the three diseases. Results show that average precision values are ranged from 90.4% to 95.6% and recall values are ranged from 89.4% to 94.7%. Hu *et al.* [8] used Faster R-CNN and VGG16 for detection and severity assessment of tea leaf blight disease, respectively. Detection average precision and the severity grading accuracy improved by more than 6% and 9%, respectively, compared to existing solutions. Pillay *et al.* [51] applied Mask R-CNN to quantify the severity of common rust disease in maize leaf. The Mask R-CNN performed better than standard image processing algorithms more than 5%. Gerber *et al.* [51] examined automated tuning of Mask R-CNN parameters which are very numerious and use also a genetic algorithm (GA) in order to enhance performance achieved in their previous work [50]. Pan *et al.* [42] proposed a two-stage model including object detection by Faster R-CNN and few-shot learning by siamese network to estimate strawberry leaf scorch severity. The proposed two-stage method achieved the highest estimation accuracy of 96.67%. **Table 3** is a summarize of theses above-mentioned works according to the year of publication, type of architecture (single or multi task), crop concerned, parts of the crop infected, diseases treated, the disease severity grades, source of the dataset, models used

Table 2. Summary of CNN-based solutions.

Article	*Année*	*Single/ Multi task*	*Crop*	*Part*	*Diseases*	*Severity Grade/ Level*	*Dataset*	*Models used*	*Results*
[18]	2017	single	apple	leaf	black rot	Healthy, Early, Middle and End	Plant Village	Lightweight CNN, VGG16, ResNet50 and Inception-V3	Best accuracy with VGG16: 90.4%
[10]	2019	Multi-task	apple, grape, cherry, peach, pepper, tomato, Strawberry, Potato, Corn curvularia, Puccinia polysora, Cercospora zeaemaydis…	Leaf	*	general and serious	Synthetic dataset from AI Challenger Global AI Contest (www.challenger.ai) and from others reseach works	PD2SE-Net50	Accuracies of 0.99, 0.98 and 0.91, respectively for species recognition, disease classification and disease severity estimation.
[12]	2020	single	Tomato	Leaf	Early Blight	healthy, mild, moderate, and severely diseased leaves	Plant Village (1000 images)	ResNet101, VGG16, VGG19, GoogLeNet, AlexNet, and ResNet50	accuracy: 94.6%
[22]	2020	single	Citrus (sweet orange)	Leaf	Huanglongbing (HLB) or Citrus Greening disease or citrus "cancer"	Early Stage, Moderate Stage, and Severely Infected Stage	Plant Village and crowdAI (5406 images)	AlexNet, DenseNet-169, Inception v3, ResNet-34, SqueezeNet-1.1, and VGG13	accuracy: 92.60%
[25]	2020	multi-task,	Coffee	Leaf	Leaf miner, rust, brown leaf spot and cercospora leaf spot	healthy (<0.1%), very low (0.1% - 5%), low (5.1% - 10%), high (10.1% - 15%) and very high (>15%).	Self-collected dataset of 1747 images	AlexNet, GoogleNet, VGG19 and ResNet50	Accuracies of 94.05% for biotic stress classication and 84.76% for severity estimation.
[14]	2020	Multi-task	corn, grap, peach, pepper, patato, strawberry, tomato	leaf	Puccinia Polysora, Curvularia Leaf Spot Fungus, Black Rot Fungus, Black Measles Fungus, Bacterial Spot, Late Blight Fungus, Early Bligh Fungus, scorch, Leaf Mold Fungus	normal, general and serious	IA Challenger (12.691 images)	BR-CNN based on DenseNet121, InceptionV3, NasNet or ResNet50	BR-CNN based on ResNet50 obtained the best accuracy (86.70%).

Continued

[24]	2020	Single	Grape	leaf	Leaf Blight	early, middle & end	Plant Village (1293 images)	AlexNet and ResNet18	AlexNet accuracy: 90.31%; ResNet accuracy: 87.6%
[4]	2021	multi-task	Pear	Leaf	Biotic stresses: leaf spot, leaf curl, and slug damage	No risk (0%), very low (1% - 5%), low (6% - 20%), medium (21% - 25%), and high (>50%)	DiaMOS Plant dataset, a self-collected dataset	ResNet50, VGG-16, VGG-19, MobileNetV2, EfficientNetB0 and InceptionV3	InceptionV3 obtained bests accuracies of 90.68% and 74.07% for biotic stress and severity estimation, respectively.
[44]	2021	single	*	*	*	*	Self-collected dataset and Plant Village dataset	Proposed lightweight CNN	accuracies of 97.9% and 90.6% on the Plant Village dataset and plant disease severity dataset, respectively
[21]	2021	single	Patato	leaf	late blight lesion	*	Self-collected dataset of 70 original images	Proposed Deep Learning algorithm	IoU values of background (soil and leaf) and lesion classes in the test dataset are 0.996 and 0.386, respectively.
[23]	2021	Single	Wheat	Leaf	Yellow rust	No disease, resistant, moderately resistant, moderately susceptible, or susceptible	Self-collected dataset of 10,500 images	Yellow-Rust-Xception	Accuracy: 91%
[11]	2021	Single	Cucumber	leaf	Angular Spot, Anthracnose, Black Spot, Brown Spot, Downy Mildew, Gray Mold, Powdery Mildew and Target Spot.	percentage	Plant Village (689 images)	proposed CNN	Accuracy: 93.75%
[38]	2021	Single	Tomato	leaf	Spotted Wilt	early, middle and least	Self-collected (3000 images)	proposed CNN	binary classification: 91.56% of accuracy and multi-classification: 95.23% of accuracy
[35]	2021	Multi-task	mustard	leaf	Downy mildew	4 severity levels	Self-collected	proposed CNN	Binary classification: 95.6% of accuracy and multi-classification: 96.66% of accuracy

Continued

[36]	2021	Multi-task	Corn/maïze	leaf	Gray leaf spot	5 severity levels	Self-collected	proposed CNN	Aaccuracy of 95.33%
[19]	2021	Single	Wheat	Spike/fruit	Fusarium head blight	0, 1, 2, 3, 4 and 5	Self-collected (3.600 images)	AlexNet and Random Forest	*
[7]	2022	single	Apple	leaf	*Alternaria* Leaf Blotch	healthy (0), early (0 - 0.95%), mild (0.95% - 1.75%), moderate (1.75% - 3.00%) and severe (3.00% - 100%)	Self-collected dataset of 5382 samples	DeeplabV3+, Unet PSPNet, VGG, ResNet and MobileNetV2	Mean accuracy of 96.41%.
[45]	2022	Single	Strawberry	Leaf	Gray mold	percentage	Self-collected dataset of 400 samples	Unet, XGBoost, K-means, Otsu	IoU accuracy, pixel accuracy, and dice accuracy are 82.12%, 98.24% and 89.71% respectively.
[46]	2022	Single	¨Paddy	Leaf	Bacterial blight	healthy, infected but disease is not severe, and infected and disease is severe	Self-collected (650 samples)	proposed-CNN	Accuracy of 97.692%
[47]	2022	Single	Patato	leaf	potato blight	1% - 20%, 21% - 40%, 41% - 60%, 61% - 80%, and 81% - 100%	Self-collected dataset (9600 images)	proposed CNN	Accuracy: 86.625%
[39]	2022	Single	Tomato	leaf	Begomovirus	4 severity levels	Self-collected	proposed CNN	*
[48]	2022	Single	Tomato	leaf	*	percentage	Internet	MRNN	*
[16]	2022	Single	Paprika	leaf & fruit	Blossom end rot, ray mold, powdery mildew, snails and slugs, spider mite, and Cercospora	11 severity levels.	Self-collected (6.000 images)	proposed-CNN	Mean average Precision: 91.7% for the abnormality detection; Mean panoptic quality score: 70.78% for severity level prediction.
[5]	2022	Single	Maize	leaf	Maydis leaf blight	low, medium and high	Self-created (1.760 images)	proposed-CNN, VGG16, VGG19, ResNet50, InceptionV3, Xception, DenseNet121, MobileNetV2 and NASNetMobile	Proposed-CNN (accuracy: 99.13% and f1_score: 98.97%)

Continued

[40]	2023	Single	Rice	leaf	Bacterial Blight	4 classes of severity	Internet (1856 images)	CNN-LSTM	Accuracy: 92%
[13]	2023	Single	Rice/Paddy	Leaf	Blast	mild, average, severe, and profound	Mendeley, Kaggle, GitHub, and UCI (1908 images overall)	CNN-SVM	Accuracy: 97%
[15]	2023	Single	Tomato	leaf	*	*	Self-collected and PlantVillage	VGG-16/VGG-19	VGG-16: accuracy of 92.46%
[2]	2023	Single	Mango	leaf	Powdery mildew	4 disease levels	Self-collected (2559 images)	CNN-SVM	Accuracy: 89.29%
[41]	2023	Single	Mango	leaf	*	beginning, mild, moderate and severe	*	proposed-CNN	*

and results obtained.

4. Limitations of Proposed Solutions and Potential Challenges

Results obtained by solutions based on IPT, classic ML and DL algorithms are very promising in crop disease severity estimation. They help to avoid yield losses, reduce production costs, ensure good disease management and so on.

However, these solutions have limitations that need to be overcome:

- For IPT-based solutions, quality of the images has a strong influence on image segmentation and, consequently, on the determination of the area infected by a disease. To obtain good results in quantifying disease severity, it is essential to use high-quality images (noiseless, without complex backgrounds, etc.).
- Estimating the severity of a crop disease from an image containing several leaves is not addressed in the reviewed works, but it is a situation that can occur in real life.
- The accuracy of severity classification increases with the severity of the crop disease. In other words, for solutions using quantitative severity levels, it is difficult to quantify disease at an early stage.
- For solutions using qualitative or quantitative severity grades, image labeling has a major impact on the classification result, and must therefore be carried out by an expert. A bad image labeling systematically leads to incorrect quantification of disease severity and, consequently, to poor a disease management.
- For solutions using the segmentation of disease lesions (on leaves, fruit, etc.), much of the edge information is lost, impacting the result of disease severity quantification.
- Crop diseases can affect leaves, fruits, flowers, panicles and so on. But until now, researchers have focused on assessing only the severity of leaf diseases.

Table 3. Summary of CNN-based segmentation networks.

Article	Year	Single/ Multi task	Crop	Part	Diseases	Severity Grade/Level	Dataset	Models used	Results
[49]	2021	Single	Wheat	Spike/fruit	Fusarium head blight (FHB)	Grade 0: [0 - 1%], Grade 1: (1% - 2.5%], Grade 2: (2.5% - 5%], Grade 3: (5% - 7.5%], Grade 4: (7.5% - 10%], Grade 5: (10% - 12.5%], Grade 6: (12.5% - 15%], Grade 7: (15% - 17.5%], Grade 8: (17.5% - 20%], Grade 9: (20% - 25%], Grade 10: (25% - 30%], Grade 11: (30% - 40%], Grade 12: (40% - 50%], Grade 13: (50% - 60%], Grade 14: (60% - 100%]	Self-collected dataset of 690 images	Mask-RCNN	accuracies of 77.76% and 98.81%, respectively for FHB detection and severity assessment.
[20]	2021	single	Rice	Leaf	Bacterial Leaf Streak	Level 0: no lesion; Level 1: lesion < 10%; Level 2 = 11% - 25% lesion; Level 3: 26% - 45% lesion; Level 4: 46% - 65% lesion; Level 5: >65% lesion.	Self-collected dataset of 109 images	Proposed Deep Learning algorithm named BLSNet and based on Unet	Average accuracy: 94%
[26]	2021	single	Coffee, Soybean and Wheat	Leaf	Coffee leaf miner, Soybean rust and Wheat tan spot	percentage	Three self-collected datasets: Coffee 406 images; Soybean 208 images and Wheat 152 images.	Unet, SegNet, PSPNet, FPN, DeepLabV3 (Xception) and DeepLabV3 (MobileNetV2)	Average precision values are ranged from 90.4% to 95.6% and recall values are ranged from 89.4% to 94.7%.
[8]	2021	Multi-task	Tea	Leaf	Leaf blight	Mild and severe	Self-collected dataset of 398 images	Faste R-CNN and VGG16	detection average precision and the severity grading accuracy improved by more than 6% and 9%, respectively, compared to existing solutions.

Continued

[50]	2021	Single	Maize	Leaf	Common Rust	percentage	Self-collected	Mask R-CNN	Mask R-CNN performed better than standard image processing algorithms more than 5%.
[51]	2021	Single	Maize	Leaf	Common Rust	percentage	Self-collected	Mask R-CNN and GA	*
[42]	2022	Multi-task	Strawberry	Leaf	Scorch	percentage	Self-collected	Faster R-CNN (VGG16) and Siamese networks	accuracy of 96.67%

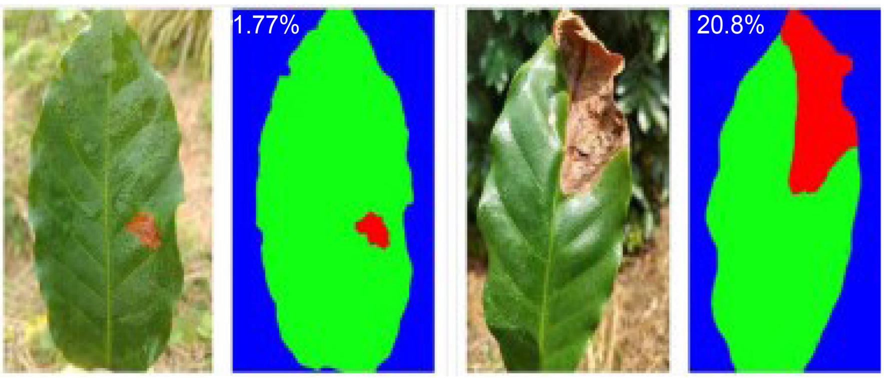

Figure 7. Example of leaf disease severity quantification based on lesion segmentation [26].

Estimating plant disease severity on other parts, such as fruits, would also be of great use in crop disease management.

5. Conclusions and Future Works

Diagnosing crop diseases goes hand in hand with assessing their severity. Estimating the severity of diseases is very useful for plant disease management. Several solutions based on IPT, ML or DL have been proposed by researchers to estimate the crop diseases severity. These solutions have achieved very impressive results, but have limitations that need to be taken into account.

For future work, we aim to propose a CNN-based solution to assess the severity of four mango fruit diseases namely anthracnose, *Alternaria*, black mould rot and stem and rot. This solution will be adapted to the reality of Africa in general, and Senegal in particular, since we will use the MangoFruitDDS dataset [52] containing images of the above-mentioned diseases and collected in an orchard located in Senegal.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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