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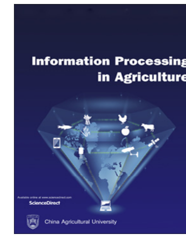

Recent advances in image processing techniques for automated leaf pest and disease recognition – A review

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Fast and accurate plant disease detection is critical to increasing agricultural productivity in a sustainable way. Traditionally, human experts have been relied upon to diagnose anomalies in plants caused by diseases, pests, nutritional deficiencies or extreme weather. However, this is expensive, time consuming and in some cases impractical. To counter these challenges, research into the use of image processing techniques for plant disease recognition has become a hot research topic. In this paper, we provide a comprehensive review of recent studies carried out in the area of crop pest and disease recognition using image processing and machine learning techniques. We hope that this work will be a valuable resource for researchers in this area of crop pest and disease recognition using image processing techniques. In particular, we concentrate on the use of RGB images owing to the low cost and high availability of digital RGB cameras. We report that recent efforts have focused on the use of deep learning instead of training shallow classifiers using hand-crafted features. Researchers have reported high recognition accuracies on particular datasets but in many cases, the performance of those systems deteriorated significantly when tested on different datasets or in field conditions. Nevertheless, progress made so far has been encouraging. Experimental results showing the leaf disease recognition performance of ten CNN architectures in terms of recognition accuracy, recall, precision, specificity, F1-score, training duration and storage requirements are also presented. Subsequently, recommendations are made on the most suitable architectures to deploy in conventional as well as mobile/embedded computing environments. We also discuss some of the unresolved challenges that need to be addressed in order to develop practical automatic plant disease recognition systems for use in field conditions.

1. Introduction

Agriculture plays a vital role in feeding both human and livestock populations globally. With the adoption of green energy

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technologies such as biodiesel fuels, the role of agriculture has expanded to clean energy generation as well. Furthermore, agriculture is also the source of raw materials used in making textiles, chemicals and medicines. In the years between the sixties and the early part of this century, agricultural production rose three-fold despite a marginal 10% increase in the amount of land under agricultural use. This was attributed to adoption of farm mechanization, development of higher yielding crop and livestock varieties and the use of fertilizers and pesticides [1]. In recent years, the rate of growth in agricultural production has been declining [2]. This trend, coupled with emerging challenges such as climate change, population growth [3], rural to urban migration and demand for biofuels pose a serious challenge to global food security.

Going forward, given that there will only be a minimal increase in the amount of land coming under agricultural use, the solution to the problem of food insecurity lies in increasing the productivity of already existing farm land. This will require the cultivation of higher yielding, faster maturing, drought and disease tolerant crop varieties and livestock breeds. Furthermore, when we consider that the global agricultural workforce is predicted to decline by 30% between 2017 and 2030 due to availability of more lucrative job opportunities in other sectors of the economy [4], adoption of technology in agriculture becomes of great importance.

Increasingly, people are now more mindful of the negative effects associated with the heavy use of chemical pesticides on personal health and the environment. Consumers are preferring organically produced foods. Moreover, regulators such as the European Union (EU) are placing ever stricter regulations on chemical usage for agricultural products entering their markets [5]. These developments are expected to occasion a roll back in the use of chemicals in agriculture, emphasizing the need for early and accurate detection of pests and diseases.

Climate change has been observed to have a close relationship to the evolution of diseases in crops, livestock and human beings [6]. Changes in weather patterns are leading to increased occurrence of pests and diseases. Often, diseases are occurring for the first time in areas where they had not been seen before [7–9]. In such cases, local farm extension officers who are not familiar with these new pests and diseases are unable to offer any support to farmers.

In response to these challenges, there is a growing interest in Precision Agriculture (PA) in order to increase yields in a sustainable way. PA is a general term that covers all techniques employed to make the management of farming more accurate and controlled [10]. These techniques include Global Positioning System (GPS) navigation of tractors, robotics, remote sensing, data analytics and unmanned aerial and terrestrial vehicles [11]. Early and accurate detection of pests and diseases is a key pillar of PA.

The application of Image Processing Techniques (IPT) and Machine Learning Algorithms (MLA) in disease detection and recognition is an active area of research that shows immense potential to address the problem of early and accurate detection of pests and diseases [7–9,12–41]. MLAs have been developed in other fields such as the ImageNet [42] challenge where accuracies that exceed human level perception have been reached. Attainment of such performance in crop pest and disease recognition is the primary objective of ongoing research efforts.

IPTs generally refer to computerized manipulation and analysis of images captured using a wide array of sensors including visible light cameras, infra-red imaging devices and sensors operating in different bands of the electromagnetic spectrum. Indeed, a lot of promising research has been carried out in the area of crop pest and disease recognition using hyperspectral techniques [43–51]. However, hyperspectral devices are expensive and not easily accessible to ordinary farmers and extension workers [52]. Therefore, the scope of this review is limited to image processing techniques employed in pest and disease recognition using visible light (RGB) images. Symptoms of plant diseases are in most cases distinctly observable on the infected plant [53,54]. Image processing algorithms can be developed to diagnose these conditions from ordinary digital photographs in a fast, accurate and cost-effective manner. Specifically, adoption of IPTs offers the following benefits:

- IPTs can be used to quickly and accurately recognize crop diseases based on images of leaves, stems, flowers and/or fruits.
- Disease severity can be estimated by calculating size of deformed or discoloured area relative to the size of the whole leaf, fruit or flower [25,32,36,37,55].
- Tracking the progression of disease in plants which is critical in detecting details such as the stage of infection and identifying symptoms that are not discernible to most human observers [16,36,56]. IPTs will also help researchers to assess the disease resistance characteristics of new crop cultivars under investigation in the lab [37].
- The information gathered through IPTs can be circulated to other people who are at remote locations quickly and inexpensively [39,40].
- Correct diagnosis will lead to more economical use of pesticides. This will lower cost of production while at the same time conserving the environment and improving accessibility to highly regulated but lucrative markets such as the EU.
- Enhanced access to human experts who can be consulted from remote locations rather than requiring extension officers to physically visit each farm [12,39].

The rest of this paper is organized as follows. In Section 2, we will review research work done so far towards the application of IPTs in crop pest and disease recognition as well as leaf identification. The performance of 10 CNN architectures on the leaf disease recognition task is compared in Section 3. Section 4, discusses gaps in the existing literature that need to be addressed in order to realize robust plant disease recognition systems. These gaps form the basis for future research work in this area. Finally, this paper concludes in Section 5.

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2. Related work

Plants infected with diseases usually exhibit visible marks or lesions on either the leaves, stems, flowers and/or fruits. Generally, each disease or pest condition presents a unique visible pattern which can be used to uniquely diagnose the anomaly. Extension officers are trained to diagnose pests and diseases by visual inspection or by conducting laboratory tests on plant samples. These approaches, however, have several limitations:

- Extension officers are often too few to cover all farms. Thus, many farmers may lack extension services at critical times [13–17,32,57].
- Training of extension officers is costly and time consuming [18].
- Farmers and extension officers may not be able to correctly recognize non-native diseases and pests [7,39].
- A high level of expertise is required to distinguish between anomalies with visually similar characteristics [13,19–22,39,58]. In such cases, even a highly trained expert may still arrive at a wrong diagnosis due to fatigue, poor illumination or poor eyesight. Moreover, individual experts are often specialists in a small set of disorders [15,18,22,59].
- Continuous monitoring is necessary for early disease detection and to prevent disease from spreading. This is tedious, time-consuming, costly and inefficient to do on an ongoing basis [13,20,22,24–29,58–60].
- In addition to the high cost of lab equipment, lab tests are destructive since they involve collecting plant samples from the field and taking them to the lab for analysis. Additionally, transportation of samples to the lab may be subject to quarantine restrictions [29].

The use of automated IPTs in crop pest and disease detection is an active area of research aimed at overcoming these limitations. The improving capability and availability of digital cameras and computing hardware coupled with their decreasing cost means that digital IPTs promise to offer a possible alternative to human expertise in this field.

In this section, we will present an overview of the work done in the field of crop pest and disease recognition using IPTs. Section 2.1 shows that early works relied on classical image processing procedures and 'hand-crafted' feature extraction from leaf images. These features were then used to train shallow classifier algorithms such as Support Vector Machines (SVM), Principle Component Analysis (PCA), Maximum Likelihood Classification (MLC), K-Nearest-Neighbours (KNN), Naïve Bayes (NB), Decision Trees (DT), Random Forest (RF) and Artificial Neural Networks (ANN) [7,12,13,19,21,30,32,36,58,61–66]. More recent works have focused on development of deep learning Convolutional Neural Network (CNN) architectures to automatically perform feature extraction and image classification [8,14–16,18,20,22,23,27–29,31,33–35,37,59,67–74]. This trend is enabled by three major factors; availability of larger datasets, adaptation of multicore Graphics Processing Units (GPUs) to training of deep neural networks and development of supporting software libraries such as Compute Unified Device Architecture (CUDA) from Nvidia corporation [75]. Section 2.2 discusses deep learning-based disease recognition techniques.

2.1. *Leaf disease recognition based on hand-crafted feature extraction*

Early works in automatic leaf disease recognition followed the general workflow shown in Fig. 1 below. Image capture involves collection of photographic information using a suitable camera. Image pre-processing is carried out on the captured images in order to improve image quality. Examples of procedures carried at this stage are image resizing, filtering, colour space conversion and histogram equalization. In plant disease recognition applications, segmentation is twofold. Segmentation is first done to isolate the leaf, fruit or flower from the background. A second segmentation is then done to isolate healthy tissue from diseased tissue.

Feature extraction involves mining of information from the segmented image which could facilitate accurate classification of the anomaly. Features that could be extracted are texture (energy, contrast, homogeneity, and correlation), shape, size and colour. Textural features can be extracted using statistical measures such as Local Binary Patterns (LBP), Grey Level Co-occurrence Matrix (GLCM), Colour Co-occurrence Matrix (CCM) and Spatial Grey Level Dependence Matrix (SGLDM). Textural features can also be extracted using model-based methods such as Auto-Regressive (AR) and Markov Random Field (MRF) models.

Machine learning algorithms are supplied with feature vectors and trained to categorize features associated with each disease to be recognized. The trained algorithm can then be used to recognize features from new images captured from the field. Classification deals with matching a given input feature vector with one of the distinct classes learned during training. The designer may use more than one learning algorithm for training and classification and fuse the results from the algorithms [7,30,36].

The study in [7] investigated the use of IPTs in recognition of three wheat diseases namely, Septoria, Rust and Tan-Spot at different stages of infection and under natural conditions. More than 3500 images were captured at two pilot sites in Spain and Germany over three years from 2014 to 2016 using various mobile devices. Area under Receiver Operating Curve (AuC) scores of 88% and 81% were reported on the validation set and during field trials respectively demonstrating that the system generalized well to field conditions. Two options were adopted for segmentation; automatic segmentation using the Simple Linear Iterative Clustering (SLIC) algorithm [76] or manual segmentation based on a user-defined region of interest followed by mask refinement using the Chan-Vese algorithm [77] based on the saturation colour channel. Further segmentation was done in order to isolate suspicious sub-regions on the leaf as disease candidates (Hot-Spots) based on colour features and a Naïve Bayes classifier which detected presence or absence of disease in the sub-images. A RF clas-

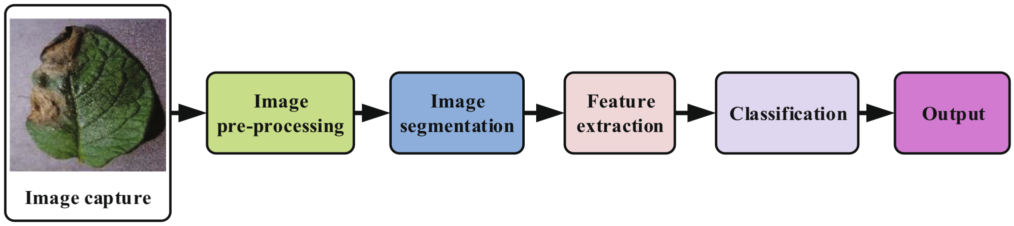

Fig. 1 – Hand-crafted feature extraction and classification workflow.

sifier then classified the disease. A meta-classifier was used to compute a confidence score for the particular disease by evaluating all the determined probabilities for the candidate regions. The system showed good performance in detecting early stage infections. Furthermore, it was reported that the use of colour constancy normalization increased the overall accuracy by about 5%. Thus, it was proved that colour constancy normalization can increase the robustness of the system to illumination variations that occur under field conditions.

The authors of [13] used a dataset of 300 potato leaves drawn from the PlantVillage dataset [78] to design a classifier capable of recognizing healthy leaves and those affected by late blight and early blight diseases. Multiclass SVM was used to classify leaf images into one of the three categories based on 10 colour and texture features. The system achieved a five-fold cross-validated accuracy of 93.7%. However, the original dataset contains 152 images of healthy potato leaves and 1,000 images each for late blight and early blight categories. It would have been more beneficial to provide the performance of the system on a larger dataset.

In [19], the authors used IPTs to diagnose powdery mildew and downy mildew from grape leaf images (35 and 50 images respectively) and wheat stripe rust and wheat leaf rust from wheat leaf images (50 images each). Classification of leaf disease was done using a Back-Propagation (BP) network with various combinations of shape, colour and texture features forming the input feature vector. The authors experimented with seven feature combinations as well as different BP network architectures and activation functions. They reported peak recognition accuracies of over 91% even after reducing the feature vector dimensionality using PCA. Qin et al. [21] proposed a solution for the recognition of four leaf diseases affecting alfalfa grass. Images were cropped to produce sub-images with one or several lesions. SVM was the best performing classification algorithm providing recognition accuracies of 97.64% and 94.74% on the training and testing sets respectively. Furthermore, dimensionality of the 45 feature vectors was reduced using PCA before classification using a Naïve Bayes classifier. An 80% recognition accuracy was reported when these reduced feature vectors were used. Tiwari and Tarun [25] proposed an algorithm based on a modified SVM classifier to recognize four leaf diseases (Alternaria Alternata, Cercospora Leaf Spot, Anthracnose and Bacterial Blight) from a dataset of 150 images. Cuckoo Search (CS) optimization algorithm was used to find the optimum classifier parameters. The authors reported an enhanced recognition accuracy of 96.5% to 98.5% attributed to the use of the CS algorithm compared to 65% to 72% accuracy achieved when using the basic SVM. Ramesh and Vydeki [79] proposed using the Jaya optimization algorithm to optimize the weights of a deep neural network employed to recognize paddy leaf diseases (bacterial blight, brown spot, sheath rot and blast diseases). K-means clustering technique was used to remove background features and isolate lesions. Two colour and four texture features were used for classification. Performance of the proposed DNN-JOA classifier was demonstrated to supersede that of ordinary Deep Neural Networks (DNN), ANN and Denoising Auto Encoder (DAE) classifiers in terms of accuracy, F1 score, precision, False Discovery Rate (FDR), False Negative Rate (FNR), Negative Predictive Value (NPV), True Positive Rate (TPR), True Negative Rate (TNR) and loss function. These studies demonstrated the fragility of systems designed using hand crafted features and shallow classifiers. Designers must try out different features and classifier parameters combinations to determine which recipe gives the best results. The authors of [21] reported that the ReliefF method [80] outperformed both the one-rule (1R) [81] and Correlation-based Feature Selection (CFS) [82] methods in terms of selecting the most robust features for classification.

Es-Saady et al. [30] proposed a system based on a serial combination of two SVM classifiers to recognize three diseases (early blight, late blight and powdery mildew) and three pest conditions (leaf miners, Thrips and Tuta Absoluta) using a dataset of 284 images. All images in the dataset were taken against a black background. Eighteen colour features were input to the first SVM classifier while 30 texture and 11 shape features were input to the second SVM classifier. The authors reported that their system had a superior recognition accuracy of 87.80% compared to other systems in literature based on SVM and ANN classifiers whose performance ranged from 74.40% to 82.93%. In [58], Padol and Yadav proposed a grape leaf disease recognition algorithm based on an SVM classifier that was trained on 9 colour and 9 texture features. A total of 137 images captured from the field or obtained from the internet were used in the study. The authors reported a mean classification accuracy of 88.89% on the test set of 27 images. The authors of [36] extended the work of [58] by using both SVM and ANN classifiers trained on the same 18 colour and texture features as [58] and fusing the results of the two classifiers. The authors reported a recognition accuracy of 100% for both downy and powdery mildew diseases when using this ensemble classifier. This was superior to the 88.89% and 91.67% accuracies achieved by individual SVM and ANN classifiers respectively. Given the correct selection of features and classifier parameters, multi-classifier systems can attain higher accuracy compared to single classifier systems.

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A study on leaf rot disease detection on betel vine leaves was conducted in [55]. The dataset was constructed by obtaining 12 infected leaves from the field and scanning them with a flatbed scanner. Otsu segmentation was performed to isolate infected tissue. Severity of infection was determined by calculating the area of the infected part relative to the size of the leaf. A performance of 100% precision and 83.33% recall was reported in this study. The simplicity of this algorithm would make it an ideal candidate for implementation on mobile devices. However, the algorithm cannot work in the presence of complex backgrounds and would require the user to place a white card board behind the leaf when capturing the image.

The studies conducted in [61,62] proposed the use Genetic Algorithm (GA) to perform segmentation of diseased parts of the leaf from healthy parts. They suggested that the superiority of the GA over K-means clustering segmentation technique was that GA did not require user input at the time of segmentation since cluster centres were initialized automatically. Moreover, the GA generated several segmentation results and automatically chose the best result. Two classifiers were considered; namely SVM and MDC. For comparison, k-means clustering was used in place of GA and classification was done using MDC. The results shown indicate that GA hybrid with SVM attained the highest recognition accuracy of 95.71%. This was superior to k-means clustering hybrid with MDC which achieved 86.54% recognition accuracy and GA + MDC which achieved 93.63% accuracy. The study in [83] proposed the use of Particle Swarm Optimization (PSO) to segment lesions from sunflower leaves. An MDC classifier was then trained to recognize 6 sunflower leaf diseases using colour and texture features. A mean accuracy of 98% was reported in [83] exceeding the performance reported in [62]. Chouhan et al. [84] proposed the use of Bacterial Foraging Optimization (BFO) algorithm to optimize a Radial Basis Function Neural Network (RBFNN) for identification and classification of six plant leaf diseases. In that study, BFO was used to initialize the weights of the RBFNN while infected regions were segmented using a Region Growing Algorithm (RGA). A dataset of 276 images was used in this study. Specificity and sensitivity were used to measure segmentation performance while recognition accuracy was measured in terms of validation partition coefficient (V_{pc}) and validation evaluation partition entropy (V_{pe}). To validate the proposed system, segmentation accuracy of the RGA was compared to that achieved by GA and K-means clustering and recognition accuracy of the RBFNN was compared to SVM and GA classifiers. The studies reported in [61,62,83,84] show that learning algorithms can be used to segment lesions from the rest of the image even under field conditions. Segmentation performance is not quantified in most cases but qualitative results show that the segmentation algorithm mistakes some background features for lesions. This has potential to lower the accuracy of the disease recognition stage which follows after segmentation.

In [63], five types of tomato diseases; namely tomato late blight, Septoria spot, bacterial spot, bacterial canker, tomato leaf curl and healthy tomato plant leaf and stem images were classified. Decision Tree algorithm comprising 83 nodes was used to classify the images based on 24 shape, colour and texture features. An average ten-fold cross validated test set accuracy of 97.3% was reported in that study.

The work of [64] introduced a new statistical-model-based feature vector derivation technique for the recognition of six tomato diseases. Generalized Extreme Value (GEV) distribution was used to reduce the dimensionality of the SIFT feature vector thereby lowering the computational requirements of the algorithm. The authors reported the 10-fold cross-validated performance of the system as 84.7% accuracy. Furthermore, an inference speed of 12,000 predictions/second was achieved by the proposed method. It took 56.8 s to train the classifier. In their subsequent work [65], the authors of [64] modelled the SIFT texture features using Johnson SB distribution for dimensionality reduction. Using the same dataset and experimental procedure applied in [64], slightly better accuracy performance of 85.1% was achieved. Training time was also reduced to 33.9 s. However, inference speed reduced to 5,700 predictions per second. Comparing the results for the best performing configurations in [64,65], it can be seen that the Johnson SB model offers better feature vector dimensionality reduction compared to the GEV model, resulting in a much shorter training time. Reliable reduction in feature vector dimensionality lowers the computational requirements of the algorithm without sacrificing accuracy. This makes the resulting algorithms more suitable for deployment in devices having limited computing resources.

Pantazi et al. [85] proposed a grape leaf disease recognition algorithm based on one-class SVM classifiers. A one-class classifier was dedicated to detect each of the six diseases considered in that study. Input images were segmented using the GrabCut algorithm [86] to remove background elements. Texture feature was extracted by computing the 32-bin Local Binary Pattern (LBP) [87] histogram from the hue component of the segmented image. Lesions associated with each disease exhibited a unique histogram signature. Each one-class SVM classifier was trained to recognize one of the 6 LBP histogram patterns. In the event of conflict between two or more classifiers, a nearest support vector strategy was employed to assign a class to the test image. The robustness of this approach was demonstrated by the fact that despite using only 8 images in each class to train the classifiers, an accuracy of 95% was still achieved on 46 test images. However, the nearest support vector strategy had to be relied on to resolve conflicts between one-class SVM classifiers in more than 50% of the test images. This is indicative of small inter-class distance and large intra-class distance caused by either relying on a brittle feature or a weakly trained classifier. Ideally, conflict resolution should be required less frequently.

Table 1 offers a brief overview of recent research works in automatic leaf disease recognition using hand-crafted feature extraction and shallow classifiers. It summarizes the pre-processing techniques, features and classifiers used, and performance of the algorithms developed in the respective studies.

Based on the foregoing, it is clear that success of the disease recognition algorithm depends on many variables that are subject to the judgement of the system designer. These include the choice of pre-processing and segmentation techniques to be used, which colour space to adopt, which features to extract and finally which learning algorithm to use

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Table 1 – Summary of recent works on leaf disease recognition using hand crafted feature extraction and shallow classifiers.

Article	Crop	Dataset	Pre-processing techniques	Features used	Classifier used	Performance
[7]	Wheat	3500 Field images	Colour constancy normalization, automatic segmentation SLIC and manual cropping of the region of interest (RoI) using the tactile screen of the mobile device and Chan-Vese algorithm, RGB to L*a*b* and HSI conversion	Colour, Texture	RF, NB	AuC: 0.82 Accuracy: 0.78 Sensitivity: 0.81 Specificity: 0.75
[13]	Potato	300 Lab images	RGB to L*a*b* conversion, thresholding to remove background and healthy parts of the leaves	Colour, Texture	Multiclass SVM	Accuracy: 0.937 Precision: 0.95 Recall: 0.95 F1 score: 0.95
[19]	Grapes, Wheat	185 Field images	Resizing, cropping, median filtering, RGB to L*a*b* conversion, segmentation using K-means clustering, hole filling using morphological operations	Colour, Shape, Texture	BP network	BP Network: Wheat: 100% accuracy Grapes: 100% accuracy PCA + BP Network: Wheat: 100% accuracy Grapes: 97.14% accuracy
[21]	Alfalfa	899 Lab images	Resizing, RGB to grayscale, L*a*b* and HSV conversion, segmentation using K-means, Fuzzy C-means and K-median clustering	Colour, Shape, Texture	SVM, NB, LDA, logistic regression analysis and regression tree. PCA used for feature dimension reduction	97.64% training accuracy, 94.74% testing accuracy using SVM and 80% accuracy using PCA/NB classifier
[25]	Potato	150 Field images	RGB to grayscale conversion, Histogram equalization, segmentation using K-means clustering	Texture	SVM with CS optimization	98.5% accuracy achieved using SVM with CS, 72% accuracy using basic SVM
[30]		Unspecified	284 Lab images	Resizing, median filtering, RGB to L*a*b* conversion, segmentation using K-means clustering	Colour, Shape, Texture	Two serially connected SVM classifiers
	87.80% accuracy					
[58]	Grapes	137 Field images	Cropping, resizing, Gaussian filtering, RGB to L*a*b* and HSV conversion, segmentation using K-means clustering	Colour, Texture	SVM	88.89% accuracy (93.33% - downy), 83.33% powdery mildew)
[36]	Grapes	137 Field images	Cropping, resizing, Gaussian filtering, RGB to L*a*b* and HSV conversion, segmentation using K-means clustering	Colour, Texture	Fused SVM + ANN classifiers	100% accuracy
[55]	Betel	20 scanned images	Resizing, RGB to HSV conversion, Otsu segmentation on H channel	–	–	100% precision 83.33% recall

[61,62]	Banana, Beans, Lemon, Rose	106 Lab and field images	Image cropping, smoothing filtering, RGB to HSI conversion, segmentation using K-means clustering compared to using GA for separation of healthy and diseased tissue	Colour, Texture	GA + SVM Compared to: GA + MDC K-means + MDC	86.54% accuracy (K-means + MDC), 93.63% accuracy (GA + MDC), 95.71% accuracy (GA + SVM)
[63]	Tomato	383 Field images	Segmentation for background removal using Otsu thresholding	Colour, Shape, Texture	Decision Tree	97.3% accuracy
[64]	Tomato	3535 Lab images (PlantVillage dataset)	Segmentation by colour thresholding, hole filling for mask refinement	Texture (SIFT with GEV distribution for dimensionality reduction)	SVM	84.7% accuracy, 9000 predictions per second
[65]	Tomato	3535 Lab images (PlantVillage dataset)	Segmentation by colour thresholding, hole filling for mask refinement	Texture (SIFT with Johnson SB distribution for dimensionality reduction)	SVM	85.1% accuracy, 5700 predictions per second
[79]	Rice	650 field images	Resizing to 300x450 pixels, RGB to HSV conversion, threshold S component at 90 to obtain background removal mask, k-means clustering using H component to separate infected region	Colour, texture	DNN-JOA validated against DNN, ANN and DAE	Accuracy: 94.25% F1-score: 88.74% Precision: 81.24% FDR: 19.64% FPR: 4.42% FNR: 8.94% TPR: 83.7% TNR: 94.04% NPV: 94.14%
[83]	Sunflower	Not specified	Median filtering, resizing images, segmentation using thresholding and PSO, RGB to HSI conversion	Colour, texture	MDC	98% accuracy

[84]	Unspecified	276 (6 from planet natural + 270 from crowdAI.org) field images	Segmentation using RGA. Compared to GA and K-means clustering	–	BRBFNN compared to SVM and GA	Segmentation specificity: RGA: 0.8558 GA: 0.8139 k-means: 0.7914 Segmentation sensitivity: RGA: 0.8705 GA: 0.8244 k-means: 0.802 Classification V_{pc}: BRBFNN: 0.8621 SVM: 0.8337 GA: 0.8113 Classification V_{pe}: BRBFNN: 0.1118 SVM: 0.1665 GA: 0.1933
[85]	18 species	48 (training), 46 (testing) field images	Segmentation using GrabCut algorithm, RGB to HSV conversion	LBP histograms	One-class SVM classifiers with nearest support vector strategy for conflict resolution	95% test set accuracy

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for classification. There is no way to tell *a priori* which combination of pre-processing, feature extraction or classification algorithms will yield the best results leading to a tedious trial and error approach when attempting automatic plant disease recognition using hand-crafted feature extraction and shallow classifiers [7,13,19,21,25,30,36,55,58,61–65,79,83–85]. Furthermore, hand-crafted methods are only successful under limited and constrained setups and fail when there are slight variations in the operating conditions [14,15,22,59]. It has also been noted that segmentation techniques give unreliable results particularly in the presence of complex backgrounds and where lesions do not have well defined edges but instead merge gradually with the healthy part of the leaf [14,88]. Moreover, some of the best features for classification cannot be extracted by hand using any of the known mathematical tools available at this time.

2.2. Leaf disease recognition using deep learning techniques

In recent years, CNNs have demonstrated outstanding performance as feature extractors and classifiers in image recognition tasks such as the ImageNet challenge. This idea has been extended to agricultural applications in order to accomplish tasks such as disease recognition, pest recognition [89,90], weed detection [91], fruit and flower counting [17,92–95] as well as fruit sorting and grading [96]. In particular, since 2015 most research in leaf disease recognition using IPTs has leveraged deep learning [15]. LeCun et al. [97] defined deep learning as a representation learning method whereby the algorithm finds the best way to represent data through a series of optimizations instead of semantic features. With this learning procedure, there is no need to do feature engineering since features are automatically extracted. Deep learning will enable advances in the agricultural industry in the fields of disease diagnosis, pest detection, quality management, marketing, automation, robotics and big data.

Large datasets comprising thousands of images are required for the training of CNNs. Unfortunately, in the field of plant disease recognition, such large and diverse datasets have not yet been assembled and availed for use by researchers. At the present time, transfer learning is the most effective way to train robust CNN classifiers for plant disease recognition. Transfer learning enables the adaptation of pre-trained CNNs by retraining them with smaller datasets whose distribution is different from the larger dataset previously used to train the network from scratch [22]. Indeed, studies show that using CNN models pre-trained on the ImageNet dataset and then retraining them for leaf disease recognition gives better results [26,31,70].

Kawasaki et al. [28] proposed a CNN architecture for cucumber leaf disease recognition capable of recognizing melon yellow spot virus (MYSV), and zucchini yellow mosaic virus (ZYMV) infection. This work showed that data augmentation has a higher contribution to recognition performance than increasing the number of training epochs. In [29], the authors extended the work of [28] by considering 7 viral cucumber leaf diseases. This time, the authors considered the effect of environmental conditions such as highlights and shadows on recognition performance. They also evaluated the effect of different image augmentation strategies (rotation, mirroring and translation) on the classifier's performance. Performance of two CNN models with respect to image condition demonstrated that the performance of CNN-2 did not deteriorate when tested on bad condition images unlike the case for CNN-1. This is because CNN-2 was trained using both good and poor condition images which made it generalize better to different illumination conditions. Conversely, CNN-1 was trained using clear, well illuminated images only and was not able to adapt well when tested with noisy or poorly illuminated images. Furthermore, the authors demonstrated that increasing the number of augmentation strategies used improved classification performance.

Nachtigall et al. [18] used a CNN to recognize diseases, nutritional deficiencies and herbicide damage in images of apple leaves. Their dataset contained 1450 images taken against a white background representing 6 categories (healthy and 5 disorders). A team of 7 professionals with expertise in different fields was used to annotate the dataset. The authors compared the recognition performance of the CNN to that of a Multi-Layer Perceptron (MLP) network trained on the same dataset and human experts' opinion. They reported that a higher recognition accuracy was achieved by the CNN compared to both the MLP network and human experts. AlexNet [98] architecture had the highest accuracy among all CNN architectures considered in that study.

In [9], the authors assembled a dataset of 4483 leaf images downloaded from the internet. They chose Caffe deep learning framework [99] and demonstrated that a pre-trained CaffeNet CNN architecture could be adapted for leaf disease recognition through transfer learning. The authors reported a top 1 recognition accuracy of 95.8% before fine tuning the model and 96.3% after fine tuning the model. In [31], Mohanty et al. used the PlantVillage dataset [78] to perform 60 leaf disease recognition experiments using AlexNet [98] and GoogLeNet [100] CNN architectures. The authors used different training-testing set distribution, different choice of training mechanism and different dataset types as shown in Table 2 below. For each configuration, training was done for 30 epochs using standardized hyperparameters in the Caffe deep learning framework. The authors reported outstanding recognition accuracy performance with mean F1 scores of over 85% in all experimental configurations. The best performing configurations attained F1 scores of over 99%. GoogLeNet trained using transfer learning consistently outperformed other configurations. Best results were also obtained by using original RGB images compared to grayscale images or segmented RGB images. Performance also increased with an increase in the ratio of images used for training to those used for testing. When the best performing model was tested with field condition images, however, accuracy fell to 31%. The ability of systems trained on a particular dataset to generalize well in varied field conditions remains an unresolved research problem.

Amara et al. [14] proposed a deep-learning CNN model based on the LeNet [101] architecture for banana leaf diseases classification. The authors experimented with both colour and grayscale images. It was reported that models trained using colour images had superior performance compared to

Table 2 – Experimental parameter configuration options [31].

Training parameter	Options
Choice of deep learning architecture	AlexNet or GoogLeNet
Choice of training mechanism	Transfer Learning or Training from Scratch
Choice of dataset type	Colour or Grayscale or Leaf Segmented
Choice of training–testing set distribution	Train:80%, Test:20% or Train:60%, Test:40% or Train:50%, Test:50% or Train:40%, Test:60% or Train:20%, Test:80%

those trained using grayscale images; a conclusion that reinforced the findings of [9,31]. Atole and Park [53] demonstrated that a pre-trained AlexNet CNN could be adapted to recognize both pests and diseases on rice crops. A dataset of 227 field images representing healthy, unhealthy and golden apple snail infested conditions was collected for this study. The fine-tuned AlexNet model achieved 91.23% test set accuracy. These studies [9,14,18,28,29,31,53] are significant for a number of reasons:

- They demonstrated that a single CNN can be trained to recognize a large number of plant anomalies across different crop species unlike classical methods using hand-crafted feature extraction and shallow classifiers [7,13,19,21,25,30,36,55,58,61–65,79,83–85] which are only able to recognize a small number of anomalies, often within a single crop.
- Use of CNNs eliminates the need for labour intensive feature engineering and complex image pre-processing procedures.
- Whereas training of CNNs is computationally demanding, requiring the use of powerful GPUs, inferences can be made on a CPU within one second.
- It is necessary to use larger datasets with high variability during training in order for the model to generalize well to new images particularly under field conditions.
- The colour feature contributes significantly to attainment of higher recognition accuracies when using CNNs.
- In light of the relatively small size of leaf disease datasets, pre-training CNNs with larger datasets such as ImageNet and then fine-tuning those networks using the leaf disease dataset results in higher recognition accuracy. In other words, transfer-learning yields better performance compared to training from scratch.

The study conducted by Durmuş et al. [71] extended the work in [31] by training SqueezeNet [102] and AlexNet CNNs on the embedded Nvidia Jetson TX1 platform [103]. Slightly lower accuracy scores were achieved by AlexNet compared to the work in [31], but this was attributed to the smaller memory size available on the embedded platform's GPU compared to what was available on the TITAN X GPU used in [31]. Comparing the performance of AlexNet and SqueezeNet models on the embedded GPU, it was seen that the deeper AlexNet model showed marginally better accuracy but had 78x larger storage requirements and 3x longer inference time. These results demonstrated that leaf disease recognition algorithms could be implemented to run in real time on low power embedded platforms. However, this work showed that even for embedded applications, higher accuracy performance could be attained by first training the model on a conventional GPU and then deploying the trained model to the embedded platform for inference tasks.

Cheng et al. [89] proposed a pest recognition system using deep CNNs. A dataset of 550 field images representing 10 pest species was collected for this study. AlexNet, ResNet-50 and ResNet-101 CNN architectures were considered in this study and their performance was compared to that of SVM and BP classifiers. The authors reported that accuracy performance of the CNNs exceeded that of both SVM and the BP network by a very wide margin. The accuracy of SVM, BP, AlexNet, ResNet-50 and ResNet-101 [104] were 44%, 42.67%, 86.67%, 94.67% and 98.67% respectively. This study also demonstrated that simply increasing the number of layers in a plain series-connected architecture such as AlexNet does not guarantee higher recognition accuracy. This is because as the network becomes deeper, it is more likely to encounter the vanishing gradient problem which makes the network difficult to train. As an example, the 9 to 11 layer modified AlexNet models showed inferior performance compared to the traditional 8 layer AlexNet architecture. The residual architecture overcomes this problem allowing deeper networks to be trained efficiently and achieve higher accuracy as was the case comparing ResNet-50 to ResNet-101.

Wang et al. [56] used the apple leaf images from the PlantVillage dataset to demonstrate that CNNs can be used to recognize disease severity. Specifically, the dataset used in this study comprised healthy leaves and those infected with black rot disease. The images were categorised as either healthy, mildly, moderately or severely infected. The authors experimented with shallow CNN architectures having 2, 4, 6, 8 and 10 convolutional layers. These networks were trained from scratch. It was reported that recognition accuracy increased with increase in network depth up to the 8 layer network but performance of the 10-layer CNN was the lowest of them all. This is probably because the 10 layer network suffered from the vanishing gradient problem as was observed in [89]. A performance comparison was also made among pre-trained VGG16, VGG19, Inceptionv3 [105] and ResNet-50 architectures. In that study, VGG16 and VGG19 models outperformed both the Inceptionv3 and ResNet-50 models.

Walleligen et al. [57] demonstrated the impact that data augmentation, batch normalization and drop out have on the performance of a CNN model. They reported that the test set accuracy of their LeNet style CNN increased from 88.2% to 98.73% after augmenting the dataset and including batch normalization in the architecture. Further improvement in performance was realized by including a dropout stage with probability of 0.5 in the fully connected layer of the CNN resulting in a final reported accuracy of 99.73%. The study by Zhang et al. [54] demonstrated that relatively shallow CNN architectures can perform comparably to larger CNN models in the disease recognition role by increasing the diversity of pooling operations and adding dropout to the dense layer of the small CNN. The authors experimented with different combinations of pooling functions in a Cifar10 CNN model and compared the performance of those networks to that of a GoogLeNet model. The Cifar10 model employing average pooling after all three convolution layers achieved a test set accuracy of 98.8% compared to GoogLeNet which achieved 98.9% accuracy. In [106], the authors investigated the effect of varying hyperparameters during training of CNNs. Wide variations in training duration and testing accuracy of VGG16 and AlexNet networks resulted from changing minibatch size, weight and bias learning rates. A rice leaf disease recognition system using a CNN was proposed by Lu et al. [72]. Shallow SVM, BP and Particle Swarm Optimization (PSO) classifiers were also trained on the same dataset for comparison with the CNN model. The authors reported that stochastic-pooling gave better recognition results and that filter kernel size did not have a significant effect on recognition accuracy. The CNN achieved a recognition accuracy of 95% compared to 92%, 91% and 88% for BP, SVM and PSO respectively. Zhang et al. [88] introduced a three-channel convolutional neural network (TCCNN) for tomato and cucumber leaf disease recognition. In that study, the authors implemented three fully convolutional feature extraction networks in parallel with a fused dense network. Each fully convolutional network received one of the three RGB colour channels. The proposed network vastly outperformed Image processing technology (IPT), global–local singular value decomposition (GLSVD), SVM, Sparse Representation based Classification (SRC) classifiers. A study of tea leaf disease recognition using deep learning was done in [107]. A Cifar10-quick model was modified by implementing two parallel convolution paths for multiscale feature extraction instead of having one set of series-connected convolution layers. In order to limit the number of learnable parameters, standard convolution layers were replaced with depthwise separable convolutions. It was reported that the modified Cifar10-quick model implementing multiscale feature extraction at the second convolution layer achieved superior recognition accuracy of 92.5% with 0.002 loss compared to the basic Cifar10-quick model and variants implementing multiscale feature extraction at the first, third and all three convolution layers. Accuracy of the best performing modified Cifar10-quick model also superseded that of LeNet-5, VGG16 and AlexNet models. These studies [54,57,72,88,106,107] demonstrated the need to try out different hyperparameter settings and network topologies when designing deep learning models for plant anomaly recognition in order to find the best performing architecture. Small CNN architectures can achieve performance levels comparable to those of more complex models if careful consideration is given to the design of the network and selection of appropriate training hyperparameters. Unfortunately, there is no known procedure for doing this except by trial and error.

Liu et al. [20] proposed a novel CNN architecture for apple leaf disease recognition. The network comprised an AlexNet-precursor network cascaded with an Inception network. The Inception network replaced the fully connected layers found in conventional AlexNet models, significantly reducing the number of learnable parameters and hence lowering storage requirements. Nesterov's Accelerated Gradient (NAG) optimization algorithm was used instead of Stochastic Gradient Descent (SDG) algorithm for updating weights in order to improve convergence speed. The performance of this network was compared with SVM, BP AlexNet, GoogLeNet, ResNet-20 [104] and VGG16 [108]. These models achieved accuracy scores of 68.73%, 54.63%, 91.19%, 95.69%, 92.76% and 96.32% respectively compared to 97.62% accuracy achieved by the proposed AlexNet-precursor + Cascade-Inception network. The proposed CNN model also had the lowest storage requirements and only AlexNet had a shorter training time.

Brahimi et al. [26] compared the performance of AlexNet and GoogLeNet CNNs trained from scratch and using transfer learning to SVM and RF classifiers for recognition of nine tomato leaf diseases. They demonstrated that pre-trained CNNs performed better than CNNs trained from scratch and that the CNN models performed better than SVM and RF classifiers. As was reported in [31], GoogLeNet had a better recognition accuracy compared to AlexNet in this study. The authors also proposed use of the occlusion method to discover how the CNN classifies diseases. However, this method is computationally expensive and its accuracy was very sensitive to the choice of hyperparameters such as shape, size and displacement stride of the occlusions. This work was extended in [27] where the authors proposed the use of saliency maps instead of the occlusion method. Guided backpropagation, which works by only allowing propagation of positive gradients during the backward pass, was shown to reduce noisy activations in saliency maps. The authors showed that the saliency map with guided backpropagation was faster and more accurate than the occlusion technique. In most studies, CNNs have been used as black boxes without a clear understanding of the inner workings of these networks. The work of [26] and [27] is critical to understanding how CNNs work to recognize diseases from images. This knowledge is key to miniaturizing CNN models.

The work of DeChant et al. [33] demonstrated that combining several CNN classifiers produced better recognition accuracy results and that it is possible to detect disease symptoms from very high-resolution images. In this work, five Stage-1 CNNs were trained to detect presence or absence of lesions associated with Northern Leaf Blight (NLB) disease in maize crops. The predictions of the three best performing CNN models were used to generate heat map images. Pixel values in the heat maps varied from 0 to 1 corresponding to the probability that a lesion was present at that location. The three heat maps resulting from Stage-1 formed the input to another CNN which made the final determination as to whether the maize was infected or not. It was demonstrated that the ensemble classifier achieved superior performance compared

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to any classifier operating in isolation. Individual CNNs achieved a maximum accuracy of 90.8%. Accuracy rose to 95.9% when two Stage-1 classifiers were used and to 97.8% when three Stage-1 classifier outputs were used.

The authors of [8],[67] and [52] adopted a different approach through the use of deep learning object detectors. In [8], Faster Region-based Convolutional Neural Network (Faster R-CNN) [109], Region-based Fully Convolutional Network (R-FCN) [110], and Single Shot Multi-box Detector (SSD) [111] architectures were used to localize the diseased region and classify the disease based on features contained inside the bounding box. Different CNN architectures were explored for use together with these detectors, namely: AlexNet, VGG-16, GoogLeNet, ZFNet [112], ResNet-50, ResNet-101[104] and ResNetXt-101 [113]. It was observed that data augmentation increased mean Average Precision (mAP) by almost 30%. Furthermore, it was found that plain CNN architectures such as VGG16 and ResNet50 performed better than deeper architectures such as ResNet-101. Higher anomaly recognition accuracy was achieved in subsequent work [67] by introducing a bank of one class CNN classifiers to refine the decision made by the Faster R-CNN. The refinement CNN filter bank suppressed false positives resulting in an improvement of 13% in mAP compared to [8]. In [52], the authors proposed SSD with inception module and rainbow concatenation (INAR-SSD). A modification to the VGG16 feature extractor used in the INAR-SSD network was done by replacing two convolution layers (Conv4_1 and Conv4_2) with inception modules. Fully connected layers of VGG16 were also replaced with 1x1 convolutions. The proposed INAR-SSD network achieved the highest mAP of 78.8% compared to Faster R-CNN and SSD networks which had mAP scores of 73.78% and 75.82% respectively. Mehmet and Kemal [35] developed an automatic detection and recognition system for leaf spot disease in sugar beet capable of recognizing 3 levels of disease severity (mild, moderate and severe). To achieve this, the authors modified the Faster R-CNN architecture by increasing the size of the input layer from 32x32 pixels to 600x600 pixels. The Updated Faster R-CNN network exhibited a lower rate of false detections than the original Faster R-CNN network. An accuracy of 95.48% was achieved by the updated model compared to 92.89% achieved by Faster R-CNN. The significance of these studies is that they demonstrated that deep learning detector networks have the ability to identify multiple infections on the same plant in a manner that is robust to intra-class variations due to the size and location of lesions on the plant and the stage of infection. Furthermore, the ability of the SSD networks in [52] to achieve over 23 FPS proves that these systems can be deployed in real time applications including disease recognition from video. A major drawback to using detectors is that dataset annotation by way of marking bounding boxes around the regions of interest is a very labour-intensive process.

In [37], a CNN based on GoogLeNet, named GPMNet, was used to develop an Automatic Phenotyping System (APS) for the *Erysiphe Necator* fungus which causes powdery mildew disease in grape vines. In this work, images of 1-cm diameter grape vine leaf disks were captured using a 46-megapixel camera. Each image was divided into 224x224 pixel non-overlapping blocks such that each image produced 864 sub-images. In all, 4000 sub-images were produced. These were then classified by three human experts as either containing fungal hyphae or not. The resulting dataset was then used to train the CNN which had two output classes (fungus present or fungus absent). The authors of [37] had to contend with variances between the human experts with respect to manual annotation of the dataset. For this reason, accuracy performance of the system varied depending on which expert's annotation was being relied on as the ground truth. Nevertheless, predictions made by GPMNet agreed with human experts' annotation on over 89% of the cases. The study was significant for a number of reasons:

1. It demonstrated that CNNs could be trained to detect microscopic features from high resolution RGB images.
2. It quantified the variation in the judgement of different human experts with respect to manual annotation of datasets. Indeed, the authors note that new methodologies should be developed to replace human experts in order to assess further improvements in AI system performance devoid of observer biases.
3. It automated and sped up the phenotyping process so that disease severity progression could be monitored quickly and accurately. This is important for researchers who are developing disease resistant cultivars.
4. When GPMNet was exposed to new fungal strains, the false negative rate of the system rose by 20% meaning that GPMNet did not generalize well to new strains which were missing from the training dataset, emphasizing the need for high variability in the dataset used for training.

Barbedo [16] proposed using images of individual lesions and spots rather than whole leaves to classify leaf disease using deep learning. The advantages of this method were that occurrence of multiple diseases on the same leaf could be detected and it ensured data augmentation by cutting up the leaf image into multiple sub-images. GoogLeNet architecture was selected due to its superior performance as reported in [31,34]. Background removal significantly increased recognition accuracy achieved by the CNN. Furthermore, classification based on cropped sub-images of affected regions was shown to improve disease recognition accuracy by 12%. The problems of accurate automatic background removal and sub-division of the images into individual lesions have not yet been resolved.

Elhassouny and Smarandache [69] demonstrated that it is possible to implement compact deep CNNs for plant disease recognition on mobile phones. In that work, MobileNets [114] was trained to recognize 10 common tomato leaf diseases using images drawn from the PlantVillage dataset. Results showed that the choice of optimization algorithm had only a mild influence on the overall accuracy of the model. Furthermore, experiments with different learning rates showed that higher accuracies could be achieved by lowering the learning rate at the expense of longer training time. Reported accuracies ranged from 85.9% to 90.3% depending on the choice of learning rate. Development of CNN models that can be deployed on mobile devices will increase the ability of farmers to access and benefit from this technology especially given ubiquity of smart phones.

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Tetila et al. [70] proposed a technique for soybean leaf disease recognition. Images were captured using a camera mounted on an Unmanned Aerial Vehicle (UAV) flying 2 m above the crop. The 300 raw images were segmented using the SLIC superpixel algorithm to form 3000 sub-images. Human experts annotated the sub-images and categorized them into six classes. CNNs which took these superpixel sub-images as input, were trained to classify the condition of the input sub-images. The authors experimented with different CNN architectures namely, Inceptionv3 [105], VGG19 [108], ResNet-50, and Xception [115] and compared their performance in terms of accuracy, training time and learning error. They also experimented with training from scratch, fine-tuning and transfer learning strategies for learning network weights and biases. Inception-v3 model trained using 75% fine-tuning strategy achieved the best recognition accuracy (99.04%) while VGG-19 trained from scratch had the worst recognition accuracy (69.59%). Generally, all models trained using 75% or 100% fine-tuning strategies attained high recognition accuracy. Even though image processing was done offline, this work showed that it is possible to deploy leaf disease recognition systems on UAVs and robots. It is also important to note that this system is predicated on prior knowledge of approximate leaf dimensions and the vertical distance between the drone and the crops in order to set the parameters of the SLIC algorithm. This limits the adaptability of this system to other field conditions. The underlying problem which remains to be resolved is automatic background removal and segmentation of individual leaves.

In [68], Arsenovic et al. introduced the use of Generative Adversarial Networks (GANs) for artificial generation of leaf images. Different GAN architectures (DCGAN [116], ProGAN [117] and StyleGAN [118]) were considered. StyleGAN was found to be the most successful at generating leaf images in the 256 $\times$ 256 pixel dimension range. Training of these GAN networks on field images was not successful because of the busy background present in field images and remains as an unresolved problem. Networks trained on the dataset which included GAN-generated images attained roughly 1% better accuracy on the test set compared to networks trained using natural images only. A novel two-stage CNN called PlantDiseaseNet (PDNet) [68] was also implemented. Stage one (PDNet-1) used a YOLOv3 [119] detector with an AlexNet feature extractor to predict leaf bounding boxes. Stage two (PDNet-2) was made up of a 32-layer residual CNN architecture, global average pooling layer, a 42-way fully connected layer and a softmax layer to perform disease classification. PDNet-1 attained a mAP score of 0.9165 while PDNet-2 had a 93.67% disease recognition accuracy. The modular design of PDNet means that it can easily be upgraded and customized for different crops, diseases and field conditions. Artificial generation of training images holds a lot of potential to address the problem of unavailability of large datasets. However, generation of artificial field condition images has not been resolved.

Picon et al. [120] extended the work of [7] by using a deep residual CNN to classify wheat leaf disease. A ResNet-50 network was modified by substituting two 3x3 convolutions for the first 7x7 convolution layer in order to extract finer visual details. Additionally, sigmoid activation was used in place of a softmax layer in order to allow for the detection of multiple diseases. The authors also experimented with replacing the dense layers of the CNN with 1x1 kernel fully convolutional layers but this had an adverse effect on the performance of the network. Another contribution in this work was that it demonstrated that training images could be augmented by adding random images in the background in order to enhance recognition accuracy under field conditions. However, background removal altogether gave more consistently reliable results. Online augmentation strategy at test time also improved recognition accuracy.

Deep learning models developed for leaf disease detection and recognition such as those presented in this survey have mostly relied on well-known CNN architectures such as AlexNet, GoogLeNet, Inception and ResNet. These architectures were developed and optimized for the ImageNet dataset which currently has over 14 million images in more than 20,000 categories. For this reason, these CNN architectures had to be very deep and have millions of learnable parameters in order to categorize images in the ImageNet dataset. In the field of plant disease recognition, however, datasets do not have as much diversity as the ImageNet dataset and as such a much leaner CNN model should suffice. Toda and Okura [73] studied this problem and recognized that when well-known CNN architectures were trained for plant disease recognition, most of the weights in the CNN were redundant. They showed that up to 75% of the network parameters can be discarded without a degradation in the model's performance. In that study, an Inceptionv3 CNN was trained from scratch using images from the PlantVillage dataset. Four broad techniques (Hidden Layer Output visualization, Feature visualization, Semantic Dictionary and Attention Map) were considered for visualizing feature maps at hidden layers within the CNN. It was discovered that Attention Map techniques Grad-CAM [121] and Explanation Map [122] offered the most descriptive layer-wise attention maps. Using these visualizations, the authors were able to determine that the feature extraction layers of their Inceptionv3 model could be truncated at the Mixed5 layer yet maintain the same level of performance (97.15% accuracy, 0.097 loss) as the original network. The resulting model had 75% fewer parameters compared to the original Inceptionv3 model.

2.3. *Hybrid leaf condition recognition techniques using both hand-crafted feature extraction and deep learning*

A number of authors [22,74], while recognizing the superiority of deep CNNs over hand-crafted feature extraction methods, have nonetheless sought to improve classifier performance by combining both feature extraction methods. They showed that obtaining the feature vector result from the CNN at the fully connected layer, combining it with a hand-crafted feature vector led to more accurate classifier performance.

In [22], Cruz et al. proposed a technique for detecting Olive Quick Decline Syndrome (OQDS) using deep learning with data fusion. The authors modified the CNN such that additional hand-crafted order statistics, texture, shape and geometric relation feature vectors were concatenated with the CNN's fully connected layers as shown in Fig. 2. It was proposed that this would enable the network to generalize better

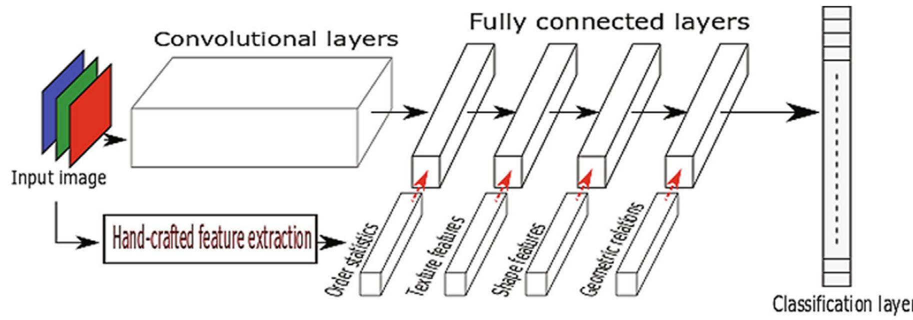

Fig. 2 – Abstraction-Level Framing model idea proposed where each fully connected layer receives additional features at increasing levels of abstraction [22].

and hasten convergence of the model even when the dataset was small. The performance of the deep learning model was compared to hand-crafted techniques used in conjunction with Radial Basis Function SVM (RBF-SVM) classifiers. The CNN showed superior recognition performance compared to the hand-crafted approaches for all scenarios where the CNN was trained for 200 epochs or more.

Çuğu et al. [74] used the Treelogy leaf dataset and experimented with different feature extractor classifier combinations as shown in Table 3. Features were extracted from the input image either by hand or using a modified AlexNet CNN. Fifteen features were extracted by hand resulting in a 56x1 feature vector. Each feature vector obtained from the CNN had a size of 4096x1. The authors showed that fusing the hand-crafted feature vector with the feature vector from the first fully connected layer (fc6) gave the highest recognition accuracy. However, fusion of the feature vector at the second fully connected layer (fc7) with the hand-crafted feature vector resulted in lower accuracy compared to using fc7 alone.

The study conducted by Kaya et al. [123] demonstrated that CNNs pre-trained on large datasets such as ImageNet and then trained on task-specific datasets could be deployed as feature extractors in conjunction with SVM and LDA shallow classifiers. In some cases these ensembles achieved higher recognition accuracy compared to CNNs on their own. Furthermore, the authors validated the idea that transfer learning improved CNN performance compared to training from scratch on a small dataset. A major limitation in these works [22,74,123] is that all images used in those studies were lab images. It is highly probable that different results would be arrived at if field images were used.

Table 4 provides a summary of recent studies conducted in crop pest and disease recognition using deep learning. Brief descriptions of datasets used in each study as well as the performance of the respective proposed algorithms are also provided. The PlantVillage dataset is the most widely used dataset in this field. Where other datasets have been collected and used on particular studies, they have not been relied upon by other researchers. Barbedo [15] noted that lack of dataset sharing between researchers is a major problem in this field. Common measures of system performance are accuracy, precision, sensitivity/recall, specificity and F1-score. In all studies where deep learning algorithms were compared to hand-crafted algorithms, deep learning provided superior recognition accuracy. Caffe and Matlab are the most widely used deep learning frameworks. Keras, pyTorch, TensorFlow and Theano frameworks have also received some attention in this field.

Fig. 3 shows that tomatoes have featured in the highest number of studies. Apples, grapes, maize and soybean are also popular among researchers in this field. Only three studies considered pest recognition. Fuentes et al. [8,67] considered pests specifically occurring in tomato crops while Cheng et al. [89] considered 10 pest species occurring in a wide range of crops. Crops such as cassava, coffee, tea, onion, passion fruit, banana, pear, coconut and olives have been considered in one study each. The works of Çuğu et al. [74] and Kaya et al. [123] focused on tree/crop leaf recognition. However, up to the current time, no works have been published for tree disease recognition using deep learning.

3. Comparative evaluation of deep learning models

A study was conducted to compare the performance of 10 deep learning models namely; AlexNet, GoogLeNet, VGG16,

Table 3 – Classification accuracies for different feature extraction and classification methods [74].

Feature vector source	Classifier	Accuracy
Hand-crafted	SVM	59.12%
First fully connected layer of the CNN (fc6)	SVM	90.37%
Second fully connected layer of the CNN (fc7)	SVM	89.62%
fc6 + hand-crafted	SVM	90.5%
fc7 + hand-crafted	SVM	89.58%
CNN *(feature extraction and classification)*		84.62%

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Table 4 – Summary of published studies in crop pest and disease recognition using deep learning techniques.

Article	CNN architecture	Validation	Deep learning framework	Crop	Dataset	Performance metric
[8]	Faster R-CNN	Different feature extractor CNNs: AlexNet, VGG-16, GoogLeNet, ZFNet, ResNet-50, ResNet-101 and ResNetXt-101	Caffe	Tomato	5000 self-acquired field images representing 9 classes of pests and diseases	mAP (0.8306)
[9]	CaffeNet (AlexNet)	none	Caffe	Apple, pear, grape, cherry, peach	4483 Self-acquired field images	Accuracy (96.3%)
[14]	LeNet	none		Deeplearning4j	Banana	PlantVillage (3700 field images)
	Accuracy (0.9861), precision (0.9867), recall (0.986), F1-score (0.9864)					
[16]	GoogLeNet	none	Matlab	14 crops	1575 self-acquired field images	Accuracy (94%)
[18]	AlexNet	MLP	Caffe	Apple	1450 Self-acquired lab images	Accuracy (96.6%)
[20]	Custom CNN (AlexNet precursor with cascade inception)	SVM, BP, AlexNet, GoogLeNet, ResNet-20, VGG16	Caffe	Apple	1053 self-acquired lab images	Accuracy (97.62%)
[22]	Modified LeNet	SIFT + RBF-SVM, background suppressing Gabor energy filtering + RBF-SVM, uLBP + RBF-SVM	Matlab	Olive	Self-acquired lab images	Accuracy (98.6%), Matthew's correlation coefficient (0.9798), F1-score (0.9689), Precision (0.9882), Recall (0.9718)
[26]	AlexNet, GoogLeNet	SVM, Random Forest	DIGITS	Tomato	PlantVillage	Accuracy (99.185%), Macro precision (98.529%), Macro recall (98.532%), Macro F score (98.518%)
[27]	AlexNet, DenseNet169, Inceptionv3, ResNet34, SqueezeNet, VGG13	none	pyTorch	14 crops, 26 diseases	PlantVillage	Accuracy (0.9976)
[28,29]	Custom CNN	none	Caffe	Cucumber	Self-acquired field images (7320 good condition images & 7520 bad condition images)	Accuracy (82.3%), sensitivity (79.9%), specificity (92.6%)
[31]	AlexNet, GoogLeNet	none	Caffe	14 crops, 26 diseases	PlantVillage	F1-score (0.9934), Precision (0.9935), Recall (0.9935), Accuracy (0.9935)
[33]	Custom ensemble CNN	none	Keras on Theano	Maize	1796 self-acquired field images (1028 infected with NLB and 768 healthy)	Accuracy (0.967)

[35]	Faster R-CNN (modified)	Faster R-CNN (unmodified)	Matlab	Sugar beet	155 self-acquired images (38 healthy, 20 mild, 35 severe, 62 mixed mild and severe infection)	Sensitivity (95.48%), Specificity (95.48%), Accuracy (95.48%)
[69]	MobileNets	none	Caffe	Tomato	PlantVillage	Accuracy (90.3%)
[70]	Inceptionv3, ResNet-50, VGG19, Xception	Transfer learning (TF), Feature tuning 25, 50, 75, 100%, No TF	Keras	Soybean	300 high resolution field images divided into 3000 superpixel images	Accuracy (99.04%), Learning error (0.049)
[68]	DCGAN, ProGAN and StyleGAN for generation of synthetic training images	AlexNet, Vgg19, Inceptionv3, DenseNet201, ResNet152	Not stated	12 crop species, 42 diseases	18,334 PlantVillage lab images + 79,265 self-acquired field images (Plant disease dataset)	Detection mAP (0.9165) Recognition accuracy (0.9367)
	Custom CNN – PDNet with Yolo/AlexNet detector and 32 layer residual classifier network					
[67]	Faster R-CNN with VGG16 feature extractor	none	Caffe	Tomato	8927 self-acquired images representing 9 anomalies and one class for background	mAP (96%)
	Custom CNN filter bank (10 CNNs)					
[37]	GPMNet – (GoogLeNet)	none	Matlab	Grape	14,180 self-acquired lab sub-images	Accuracy (94.3%), AuC (0.984)
[52]	INAR-SSD	Faster R-CNN, SSD, R-SSD	Caffe	Apple	2029 lab and field images	mAP (78.8%) Detection speed (23.13 FPS)
[53]	AlexNet	none	Not stated	Rice	227 self-acquired images (both pest and disease)	Accuracy (91.23%)
[54]	Modified Cifar10	Basic Cifar10 and GoogLeNet CNNs	Caffe	Maize (8 diseases + healthy)	500 images	Accuracy (98.9%)
[56]	Custom CNN	VGG16, VGG19, Inceptionv3, ResNet-50	Keras on Theano	Apple	PlantVillage (healthy & black rot images)	Accuracy (90.4%)
[57]	Custom CNN	none	Not stated	Soybean	PlantVillage	Accuracy (99.21%), Recall (0.99), Precision (0.99) F1-Score (0.99)
[71]	AlexNet, SqueezeNet	none	Caffe on Nvidia Jetson	Tomato	Plantvillage	Accuracy (0.943)
[72]	Custom CNN	BP, SVM, PSO	Matlab	Rice	500 self-acquired field images representing 10 rice diseases	Accuracy (95%), Missing report rate (0), False report rate (0)
[73]	Modified Inceptionv3	Inceptionv3	Keras on TensorFlow	Tomato	PlantVillage	Accuracy (0.971)
[74]	CaffeNet up to fc layers + hand crafted features + SVM classifier	Hand crafted + SVM, CNN, fc6/7 + SVM	Caffe	Trees – 57 species	PlantNet, Flavia and LeafSnap + self-acquired images	Accuracy (99.68%)

[88]	Custom 3 channel CNN	Image processing technology (IPT), Global-Local Singular Value Decomposition (GLSVD), SVM, Sparse Representation Based Classification (SRC)	Matlab	Tomato, cucumber	PlantVillage (tomato), 500 self-acquired images (cucumber)	Accuracy (94.15% for cucumber and 91.16% for tomato)
[89]	AlexNet, ResNet-50, ResNet-101	SVM, BP	Caffe	Pests	550 self-acquired field images (10 species each having 55 images)	Accuracy (98.67%)
[106]	VGG16, AlexNet	none	Matlab	Tomato	PlantVillage (6 tomato diseases + healthy)	Accuracy (96.19%)
[120]	Modified ResNet-50	Shallow classifiers in [7], ResNet-50 with fully convolutional dense layer	TensorFlow	Wheat	8178 self-acquired images (3338 Rust, 2744 Septoria, 1568 Tan Spot, 1116 healthy)	AuC (0.97), Sensitivity (0.91), Specificity (0.95), Balanced accuracy (0.93)
[107]	Modified CIFAR10-quick CNN	LeNet-5, AlexNet, VGG16, BP, Bayesian, SVM, KNN classifiers	Matlab	Tea	144 self-acquired images (36 images each of healthy, tea leaf blight, tea bud blight, tea red scab)	Accuracy (92.5%), Loss (0.002)
[123]	AlexNet, VGG16	Fine tuning, training from scratch, CNN feature extractors + SVM/LDA, CNN feature extractors + RNN	Not stated	14 crop species, 87 tree species obtained from 3 public datasets	PlantVillage (54,306 images), Flavia (1907 images), Swedish leaf dataset (1125), UCI leaf dataset (443 images)	Accuracy Flavia –VGG16 + LDA (99.10%), Swedish leaf – VGG16 (99.11%), UCI leaf – AlexNet + LDA (96.2%), PlantVillage – VGG16 (99.8%)
[124]	Custom CNN (MCNN)	PSO, SVM, RBFNN	TensorFlow	Mango	2200 images (512 healthy mango, 558 infected mango, 520 other leaves healthy, 610 other leaves infected)	Accuracy (97.13%), Missing report rate (2.87), False report rate (0)

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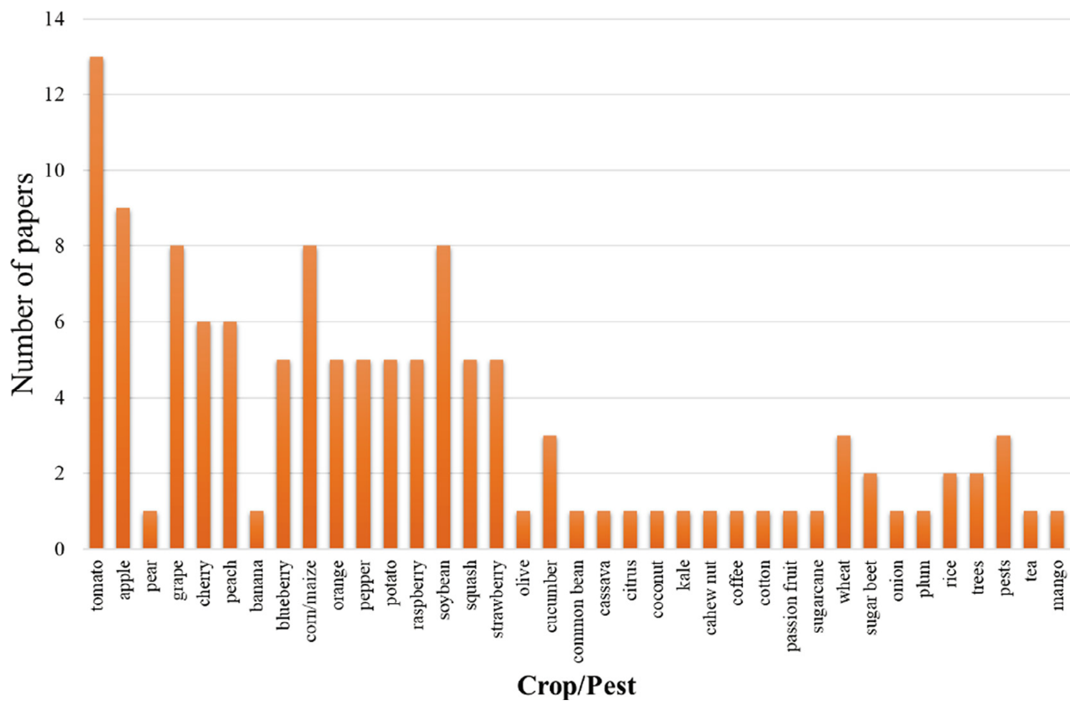

Fig. 3 – Summary of crops considered in various published works investigating crop pest and disease recognition using deep learning.

ResNet-101, DenseNet201 [125], Inceptionv3, InceptionResNetv2 [126], ShuffleNet [127], SqueezeNet and MobileNets on the leaf disease recognition task using the PlantVillage dataset [78]. Similar comparative studies using this dataset were reported in [27] and [128]. However, the work presented in this study considered a greater number of CNN models and performance metrics than earlier works.

3.1. *Materials and methods*

The dataset used in this comparative study contains 54,305 leaf images representing 14 crop species and 26 diseases. All images in the dataset were captured under controlled conditions against a uniform background, resized to a dimension of 256x256 pixels and organized into 38 classes. Each class in the dataset was split into three subsets namely; training set, validation set and testing set with a ratio of 70%, 15% and 15% respectively. Thus, the training set comprised 38,009 images while validation and testing sets each had 8147 images. These sets were used to train, validate and test all 10 CNN models in order to avoid bias.

3.2. *Experimental setup*

The experiments were performed on a computer having an AMD Ryzen 7 2700 CPU, 64 GB RAM and Nvidia RTX 2060 GPU using the deep learning toolbox in Matlab2019b running on Windows 10. A 100% fine-tuning strategy was adopted to retrain the models which were already pre-trained on the ImageNet dataset. This means that none of the layers in the pre-trained networks were frozen, and as such the back propagation algorithm would be able modify all weights and biases in the network. All models were trained for 30 epochs using the same hyperparameters as indicated in Table 5. No data augmentation was done.

3.3. *Results and discussion*

Validation accuracy and cross entropy loss for all 10 CNN models are shown in Fig. 4. It can be seen that all models converged by the 15th epoch of training and achieved accuracies of over 98.5%. Deeper models such as DenseNet201, VGG16 and ResNet-101 achieved the highest accuracy compared

Table 5 – Training hyperparameters.

Hyperparameter	Value
Learning algorithm	Stochastic Gradient Descent with momentum (SGDm)
Momentum	0.9
Minibatch size	20
Initial learning rate	0.0005
Leaning rate decay	10% every 5 epochs

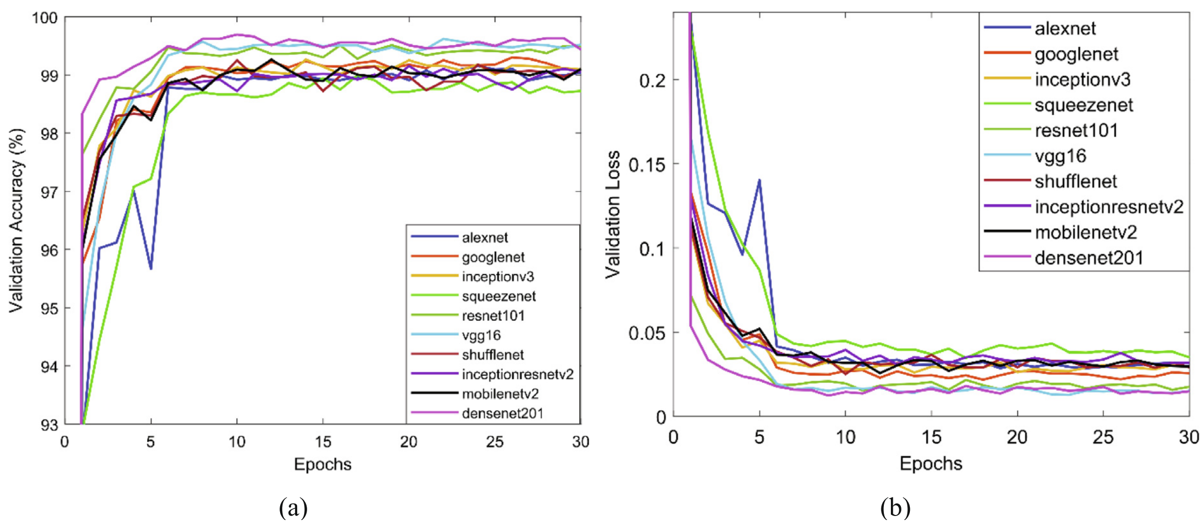

Fig. 4 – (a) Validation accuracy and (b) validation loss of 10 CNN architectures.

shallower networks such as AlexNet and SqueezeNet. Deeper networks also generally converged in fewer epochs compared to their shallower counterparts.

Test set performance for respective networks is given in Table 6. DenseNet201 out performed all other architectures on every metric. ResNet-101 matched the performance of VGG16 despite having 67.7% fewer learnable parameters (refer to Table 7). Furthermore, VGG16 is very expensive to train as evidenced by the long training duration of over 129 h compared to the 24.48 h required to train ResNet-101. The dense nature of the connections in the DenseNet201 architecture is likely responsible for the longer training duration compared to that of Inceptionv3 even though Inceptionv3 has more parameters than DenseNet201.

Table 6 – Test set performance of 10 CNN models considered in this comparative study.

CNN Architecture	Performance Metric				
	Accuracy	Precision	Recall	Specificity	F1 Score
AlexNet	0.9897	0.9871	0.9843	0.9997	0.9856
GoogLeNet	0.9899	0.9891	0.9874	0.9997	0.9881
Inceptionv3	0.9948	0.9926	0.9906	**0.9999**	0.9916
SqueezeNet	0.9837	0.9785	0.9791	0.9996	0.9787
ResNet-101	0.9951	0.9924	0.9936	**0.9999**	0.9929
VGG16	0.9951	0.9928	0.9932	**0.9999**	0.9930
ShuffleNet	0.9929	0.9895	0.9901	0.9998	0.9897
InceptionResnetv2	0.9930	0.9901	0.9887	0.9998	0.9893
MobileNetv2	0.9905	0.987	0.9857	0.9997	0.9862
DenseNet201	**0.9973**	**0.9958**	**0.9965**	**0.9999**	**0.9961**

Table 7 – Comparison of training duration, storage requirements and number of learnable parameters.

CNN Architecture	Training duration (h)	Storage requirements (MB)	Parameters (Millions)
AlexNet	1.75	227	61
GoogLeNet	4.71	27	7
Inceptionv3	22.59	89	23.9
SqueezeNet	2.19	4.6	1.24
ResNet-101	24.48	167	44.6
VGG16	129.28	515	138
ShuffleNet	6.96	6.3	1.4
InceptionResnetv2	62.4	209	55.9
MobileNetv2	8.62	13	3.5
DenseNet201	82.79	77	20

Among the larger CNN models, it would appear that DenseNet201, Inceptionv3 and ResNet-101 are the most suitable for implementing a leaf disease recognition system based on deep learning. DenseNet201 holds the advantage of having the best performance and least storage requirements but with the disadvantage of having the longest training time among the three architectures. On the other hand, Inceptionv3 has the least training time of the three models and does not require as much memory space as ResNet-101. Though the ResNet-101 model has the highest storage requirements among the three models, its accuracy is second only to that of DenseNet201. Furthermore, ResNet-101 can be trained in quarter the duration required to train DenseNet201. The studies in [73] and [120] have demonstrated that similar or better performance can be achieved by modified Inceptionv3 and ResNet architectures respectively compared to the original architectures. Therefore, careful consideration should be given when choosing among these three networks given that each architecture offers some advantages and suffers some limitations.

Small CNN architectures are desirable in mobile and embedded applications where computing resources are constrained. ShuffleNet, SqueezeNet and MobileNets could be considered for deployment in such applications due to their low storage requirements and short training durations while still achieving high accuracy. In particular, ShuffleNet had superior performance compared to SqueezeNet and MobileNets while limiting storage requirements to just 6.3 MB. SqueezeNet is an attractive option in applications having severely constrained computation capability because of its minimal storage requirements of 4.6 MB and fast training time of 2.19 h. MobileNets did not appear to offer any advantage over ShuffleNet and SqueezeNet. MobileNets had the highest storage requirements and longest training time among the three compact architectures yet had lower performance compared to ShuffleNet.

4. Unresolved challenges and open research questions in the area of plant disease detection and recognition using IPTs

A number of challenges are yet to be addressed in the literature available up to this point. Meeting these challenges is key to the design of practical leaf disease recognition systems capable of functioning in diverse field conditions with high accuracy.

4.1. *Lack of sufficiently large datasets*

Lack of large, well annotated image datasets with a high degree of variability is the main obstacle in training deep learning systems for plant disease recognition [15,16,27,129,130]. At the present time, the PlantVillage dataset [78] and the Image Database of Plant Disease Symptoms (PDDB) dataset [131] remain the only large freely available datasets. Indeed, [16,132] note that as long as sufficient data is available, deep learning techniques are well suited to plant disease recognition tasks. However, data collection from the field is laborious, expensive and requires domain experts for accurate annotation. Crowd sourcing [22,27] and free sharing of already available datasets [15,16] have been proposed as solutions to this problem.

4.2. *Data augmentation*

In the absence of large datasets, data augmentation has been proven to significantly improve the model's performance [8,9,20,22,28,29,31,68]. Arsenovic et al. [68] proposed the use of GANs to artificially generate more images for training. Their method generated leaf images on uniform backgrounds. More work is needed to artificially generate images with complex backgrounds and variations in pose and illumination. Barbedo [16] suggested disease recognition based on individual spots and lesions as another approach to augment data. Indeed, [16] showed that doing this also improved recognition accuracy by 12% in part due to the massive expansion in dataset size resulting from sampling individual spots on the leaves. Development of suitable techniques to automatically crop leaf images around the affected regions has also not been done at the present time.

4.3. *Image segmentation*

Segmentation of leaves from busy backgrounds can improve recognition accuracy [7,15,16,70]. It has been suggested that in mobile applications, users can manually crop the leaf image around the area of interest prior to disease identification. This, however, limits automation of leaf disease recognition technology and its application in UAVs and robots [16,26,27]. Moreover, an inexperienced user may still be unable to benefit from such a system where he/she has to manually highlight the region of interest. Thus, there is a need to develop reliable automatic segmentation techniques for background removal and leaf isolation.

4.4. *Recognition of anomalies with visually similar symptoms*

In cases where symptoms presented by different anomalies are visually very similar, the classifier may be unable to distinguish between them [16]. Exploitation of multiple information sources such as geographic location, weather trends, crop development stage and historical pest and disease incidence data to augment visible cues will help to arrive at more accurate predictions [16,27]. At the present time, no works have been reported in literature that incorporate these supplementary sources of information into the disease diagnosis process.

4.5. *Recognition of pests and diseases on other parts of the plant*

Researchers have so far focused on detection and recognition of diseases on the upper side of the leaf. Disease recognition from images of stems, fruits and flowers has not received much attention. Fuentes et al. [8,67] proposed techniques that could detect multiple diseases at different locations on tomato plants using Faster R-CNN networks. The techniques, though highly accurate, require painstaking labelling and annotation of the dataset. This, in our view, would limit the scalability of this approach. Brahimi et al. [27] proposed development of detectors that can be trained using simple images and then applied to detect and recognize pests and diseases in complex images.

4.6. Development of compact deep learning models for disease detection

Most deep learning-based solutions presented in literature have relied on well-known CNN architectures such as AlexNet, GoogLeNet, VGG, ResNet and Inceptionv3. This can be attributed mainly to the lack of sufficiently large datasets to train customized CNN architectures for plant disease recognition from scratch. Well known architectures provide a way around the problem of insufficient amounts of training data through the use of transfer learning techniques [26]. However, these well-known CNN models are very computationally demanding and overly complicated for the plant disease recognition task. In [73], the authors demonstrate that up to 75% of the Inceptionv3's network weights can be removed without loss of network performance. Lu et al. [72] posed the question: "How many layers and how neurons are optimal at last?" This is the dilemma faced by researchers who opt to design custom CNN classifiers forcing the designers to adopt a trial and error strategy when searching for the best performing architecture. They are also not able to take advantage of transfer learning from larger, more diverse datasets such as ImageNet and hence, their models are more likely to be over fitted. The procedure proposed in [73] should be standardized in order for it to become a part of the system development life cycle in this research area to realize accurate, compact models that are not over fitted. Compact CNN models will be highly desirable especially in embedded, robotic and mobile applications where real-time performance and low computational cost are required.

5. Conclusion

In this paper, we have presented a comprehensive review of recent research work done in plant disease recognition using IPTs. We have reported the performance of the different designs documented in recent literature. We have seen that deep learning techniques have superseded shallow classifiers trained using hand-crafted features. Provided sufficient data is available for training, deep learning techniques are capable of recognizing pests and diseases with high accuracy. The importance of collecting large datasets with high variability, data augmentation, transfer learning and visualization of CNN activation maps in improving classification accuracy has been discussed. A comparative performance evaluation of 10 state-of-the-art CNN models on the leaf disease recognition task has been conducted. The comparison has been quantified in terms of 7 performance metrics. We know of no other studies in the existing literature that provide a more comprehensive comparison of this kind. Following from this performance comparison, we have reported that DenseNet201, ResNet-101 and Inceptionv3 CNN architectures are the most suitable models for use in normal computing environments while ShuffleNet and SqueezeNet are the best suited architectures for mobile and embedded applications.

Gaps in the existing literature have also been highlighted with a view to guide future research work in this field. Future research efforts should strive towards collection of large and diverse datasets that are widely circulated in order to foster research in this field. In order to encourage adoption of these technologies in mobile and embedded platforms, there is a need to develop compact CNN models that are still able to achieve high accuracy. Future research efforts should also focus on developing reliable techniques for background removal and incorporation of other forms of data such as geographic location, disease incidence history and weather trends in order to enhance accuracy and reliability of the disease recognition systems. Recognition of disease symptoms occurring on other parts of the plant such as fruits, flowers and stems has not been extensively addressed by researchers. In this era of climate change, incidence of pests is on the rise and people are looking to increase tree coverage in order to mitigate global warming. Therefore, disease recognition in trees and pest recognition should receive more attention among researchers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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