



Machine learning for leaf disease classification: data, techniques and applications

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Abstract

The growing demand for sustainable development brings a series of information technologies to help agriculture production. Especially, the emergence of machine learning applications, a branch of artificial intelligence, has shown multiple breakthroughs which can enhance and revolutionize plant pathology approaches. In recent years, machine learning has been adopted for leaf disease classification in both academic research and industrial applications. Therefore, it is enormously beneficial for researchers, engineers, managers, and entrepreneurs to have a comprehensive view about the recent development of machine learning technologies and applications for leaf disease detection. This study will provide a survey in different aspects of the topic including data, techniques, and applications. The paper will start with publicly available datasets. After that, we summarize common machine learning techniques, including traditional (shallow) learning, deep learning, and augmented learning. Finally, we discuss related applications. This paper would provide useful resources for future study and application of machine learning for smart agriculture in general and leaf disease classification in particular.

Keywords Plant pathology · Leaf disease · Machine learning · Deep learning · Augmented learning · Smart agriculture

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1 Introduction

In recent years, Machine Learning (ML) has been emerging as a game changer in multiple aspects of life. In agriculture, machine learning has been widely used as an effective means of production, including but not limited to automatic harvesting machines, production estimation, pest control, weeds control, irrigation control, plant pathology (leaf disease classification), and fruit classification. Generally, diseases of a plant can react in different parts, such as its leaves, flowers and roots. Among them, plants' leaf is one of the most dominant and pronounced parts. Because leaves can participate in providing the nutrients the plant needs to grow, which is the photosynthesis in leaves produces the chlorophyll from sunlight Chouhan et al. (2020). Some disease of leaves may cause their drop or wither, directly affecting the plant's yield and even survival. Furthermore, it will bring negative impacts, leading to crop productivity decrease, and production costs rise. In the past, farms generally rely on labour and experts for routine inspections and disease management. Their disadvantages are obvious. First, lots of manpower and costs are required. Second, labours need training and easily get fatigued on manual jobs. Third, it is difficult to detect leaf disease timely and on a large scale. Forth, diagnosis may be subjective due to human errors and bias. Thus, an effective leaf disease classification approach is the most basic need for plant cultivation. Fortunately, ML approaches have been recently emerging as a better solution compared to traditional methods, showing their effectiveness and ease of use in plant leaf pathology classification through plant leaf image analysing. Plant leaf images have several advantages. Datasets of leaves are relatively easy to collect, analyse and reproduce (e.g., using a camera). We can also extract useful features (e.g., species, healthy states, age, and disease categories), which would improve the quality and quantity of agricultural production. Therefore, efficient and timely identification and classification of plant diseases will be the key to remedying the loss of production. Nowadays, with the introduction of precision agriculture (PA) or smart agriculture (SA) Vijaykanth Reddy and Sashi Rekha (2021); Gajjar et al. (2021); Chouhan et al. (2021); Mureşan et al. (2020); Chouhan et al. (2020); Bangari et al. (2022), ML technologies were researched and employed, especially in plant leaf pathology classification. Combine with Big Data and Internet of Things (IoT), ML can automatically detect plant leaf diseases as early as possible. Currently, the applications of ML have been deployed in various hardware and software, e.g., mobile phone applications Paymode et al. (2021), websites Wadhawan et al. (2020) and smart glasses Ponnusamy et al. (2020). With the increasing demand of ML in smart agriculture, a comprehensive survey on leaf disease classification will be beneficial to interested researchers and farmers. This paper would provide the research and industry communities with useful information on the available data and techniques, their advantages and weakness, and their applicability.

In recent years, there has been a growing interest in utilising machine learning for leaf disease classification. Several surveys have been conducted on this research topic; however, we have identified certain limitations within the reviewed works. The scope of the reviewed papers was often narrow, failing to encompass the broader concept of machine learning in leaf disease classification. Additionally, many of the reviewed papers were outdated, indicating a need for more up-to-date research in this area. Furthermore, a comprehensive review of available datasets for leaf disease classification is still lacking. It is also necessary to conduct a thorough review of the various machine learning approaches that have been employed. Currently, recent surveys have predominantly focused on emerging deep learning techniques, such as Convolutional Neural Networks (CNN). However,

due to the diverse techniques and datasets used in each survey, it remains challenging to analyze and compare research outcomes. Moreover, while numerous software applications of machine learning for pathology, including leaf-disease analysis, have been developed recently, there is a lack of comprehensive review in this specific domain.

This paper will provide a comprehensive view of current achievements and trends in the application of ML for leaf disease classification. Currently, leaf disease classification approaches can be categorised into traditional (shallow) ML, Deep Learning (DL) and Augmented Learning (AL). DL is a branch of ML and AL is a research topic, aiming to improve the effectiveness and usefulness of ML approaches. In shallow learning, feature extraction plays an important role which, in many cases, requires experts' involvement, i.e. to engineer useful features. Deep learning, on the other hand, may reduce the cost of feature engineering as it can facilitate effective learning over a large amount of data. Although, data-hungry sometimes is an issue in deep learning, leaf images are sometimes easy to collect and farmers can help with disease annotation. However, to reduce the reliance on the labelled data, data augmentation methods have been taken to produce more training data and enhance the model robustness. Transfer learning is also a promising approach for this task, as it can reduce the need for leaf data by utilising pre-trained models from other tasks. As we can see, the keys to the success of ML approaches are the quality and quantity of data. Therefore, different from the other previous surveys, we discuss the availability and quality of public datasets and their suitability for evaluating ML models.

The organisation of the paper is as follows. In the next section, we will explain how we collect and analyse related literature. Section 3 will discuss the gaps in existing review and survey papers. After that, Sect. 4 presents the available public datasets for leaf disease classification. This would help researchers to find, apply, and evaluate their ideas quickly. In Sect. 5, we categorise and compare machine learning approaches, by dividing them into three main groups: traditional (shallow) ML approaches, deep learning (DL), and transfer learning (TL). In Sect. 6, we present related applications available for leaf disease classification in real-life. Finally, Sect. 7 will summarise our findings and discuss the potential directions for future work on this research topic. This paper aims to provide some useful resources for the study and application of leaf disease classification with machine learning.

2 Methodology

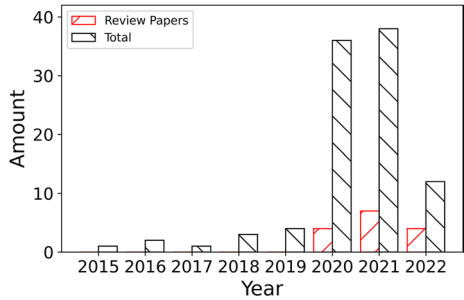
This study was researched through a series of well-known databases, including EBSCO host, Scopus and Google Scholar. The search keywords were including “leaf disease”, “plant disease”, “machine learning”, “deep learning”, “classification”, “detection”, etc. In this review, we firstly focus on quality papers by filtering them using 3 metrics: (1) number of citations; (2) rank of the published venues (Q1 for journals, and rank CORE A/A* for conferences); and (3) relevance. In addition, beyond the criteria, we also studied as many relevant articles as we could find to avoid the issue of omission. As shown in Table 1 and Fig. 1, the academic articles referenced mainly focus on the recent years (2015–2022). In Table 1, the review papers are denoted with asterisks. Out of the total papers published from 2020 to 2022, there are 15 review papers and 71 technical papers. In Fig. 1, the amount of papers shows an increasing trend year by year, which reflects the growing interest in plant leaf detection and classification. As we can see, the number of papers increases substantially in recent years, showing a growing interest in this topic.

Table 1 The publication years of Referenced Academic Articles

Year	Paper	Tech	Review	Total
2022	Meire and Sawarkar (2022) ^a , Bangari et al. (2022) ^a , Naik et al. (2022), Shaji and Hemalatha (2022), Sai Reddy (2022), Raja et al. (2022), Panwar et al. (2022), Lamba et al. (2022), Kumar et al. (2022) ^a , Bhujel et al. (2022), Bhagat (2022) ^a , Albattah et al. (2022)	8	4	12
2021	Appalanaidu and Kumaravelan (2021) ^a , Sujatha et al. (2021), Vijaykannth Reddy and Sashi Rekha (2021), Shahidur Harun Rummy et al. (2021), Dang-Ngoc et al. (2021), Jepkoech et al. (2021), Moyazzoma et al. (2021), Raina and Gupta (2021) ^a , Paymode et al. (2021), Guan (2021), Krishnamoorthy and Parameswari (2021), Kibriya et al. (2021), Chowdhury et al. (2021), Saraswathi et al. (2021), Sharma et al. (2021), Jana et al. (2021), Mukhopadhyay et al. (2021), Li et al. (2021) ^a , Chouhan et al. (2021), Gajjar et al. (2021), Jennifer et al. (2021), Ramya et al. (2021), Hu et al. (2021), Jayaprakash and Balamurugan (2021), Hassan et al. (2021), Nagaraju et al. (2022), and Navarathna (2021) ^a , Sai (2021), Kathiresan et al. (2021), Bifta Sama et al. (2021), Nagaraju et al. (2022), Divya et al. (2021) ^a , Agarwal et al. (2021) ^a , İmit Atilla Uçar et al. (2021), Mohona et al. (2021), Ahil et al. (2021), Kumar and Singh (2021), Metre and Sawarkar (2021) ^a , Ahmed and Reddy (2021)	31	7	38
2020	Xie et al. (2020), Lu and Young (2020) ^a , Singh et al. (2020a), Nagaraju et al. (2020), Kirti Rajpal (2020), Bharate and Shirdhonkar (2020), Barburiceanu et al. (2020), Huang et al. (2020), Thet et al. (2020), Lauguico et al. (2020), Singh et al. (2020b), Bhowmik et al. (2020), Ashok et al. (2020), Kumar et al. (2020a), lakshmi and Nickolas (2020), Kawatra et al. (2020), Meeradevi et al. (2020), Kumar et al. (2020b), Surya and Gautama (2020), Wadhawan et al. (2020), Nalawade et al. (2020), Nooraiyeen (2020), Rajesh et al. (2020), Kaushik et al. (2020), Sunil et al. (2020), Chaudhari and Patil (2020), Bir et al. (2020), Das et al. (2020), Ponnusamy et al. (2020), Mureşan et al. (2020) ^a , Gadade and Kirange (2020), Sharma et al. (2020), Agarwal et al. (2020), Anandhakrishnan and Jaisakthi (2020), Nisar et al. (2020) ^a , Chouhan et al. (2020) ^a	32	4	36
2019 – 2015	Geetharamani and Pandian (2019), Agarwal et al. (2019), Tulshan and Raul (2019), Mwebaze et al. (2019), Zhang et al. (2018), Sardogan et al. (2018), Paddol and Yáдав (2016), Hughes and Salathie (2015), Hughes and Salathe (2016), Wiesner-Hanks et al. (2018), Prajapati et al. (2017)	11	0	11

“Tech” column shows the number of technical papers, while “Review” column shows the number of review papers. The total number of papers we study in each year is in “Total” column
 “Review papers

Fig. 1 The amount and years of referenced articles. The red color indicates the number of review paper on leaf disease classification. (Color figure online)



3 Related work

As the interest in leaf disease classification with machine learning has been increasing recently, there are several surveys related to this research topic. In this section, we analyse recent review papers about leaf disease classification or classification. Table 2 shows their study and the gaps they left behind. As we can see, the previous surveys focused on different aspects of leaf disease classification, shedding light on some key areas in the research topic but a comprehensive study is still missing.

First, we found that many related works have a shadow scope for their study. The number of papers for review is not adequate to cover the broad concept of ML in leaf disease and many papers used in the reviews are not up-to-date. For example, In Raina and Gupta (2021); Ekanayake and Nawarathna (2021), no more than 20 articles are selected from Google Scholar for their study. Another survey paper Nisar et al. (2020), published in 2020, analyse articles all before 2017. Mureşan et al. (2020) analysed 26 academic papers about leaf disease detection and classification from 2015 to 2020. Applalanaidu and Kumaravelan (2021) surveyed more than 45 academic papers about plant disease detection and classification from 2017 to 2020. Agarwal et al. (2021) has 12 papers focusing on deep learning techniques only. In Kumar et al. (2022), they review shallow ML (10 articles) and DL (20 articles, including TL). Metre and Sawarkar (2022) surveyed about image processing with ML (3 articles), DL (5 articles) and SI (5 articles). Bangari et al. (2022) just includes 8 articles about the potato leaf disease classification results. In a recent survey Bhagat (2022), 179 papers have been studied, however, there are only 12 articles are from recent years (2020–2022) and not all of them are about leaf disease classification (the survey also covers plant species classification). Different from it, our paper focuses on more recent studies.

Second, we found that a comprehensive review about the available datasets of leaf disease classification is still missing. Many researchers already noticed that the primary obstacle in this research topic is the availability of datasets Chouhan et al. (2020); Kumar et al. (2022); Li et al. (2021); Agarwal et al. (2021). For example, Lu and Young (2020) surveyed 34 agricultural datasets, however, there is only one dataset, the Maize Leaf (NLB) Wiesner-Hanks et al. (2018), which is related to leaf diseases. Unfortunately, many datasets introduced in related work listed here are private Chouhan et al. (2020); Mureşan et al. (2020); Kumar et al. (2022); Agarwal et al. (2021). Plant Village is one of the most popular public datasets Raina and Gupta (2021); Ekanayake and Nawarathna (2021); Agarwal et al. (2021); Kumar et al. (2022); Metre and Sawarkar (2022); Bangari et al. (2022); Agarwal

Table 2 Recent review papers

Paper	Year	Strength	Limitation
Metre and Sawarkar (2022)	2022	Detailed plant leaf disease introduction	Small number of articles, image processing with ML (3 articles), DL (5 articles) and SI (5 articles)
Bangari et al. (2022)	2022	Focus on potato leaf diseases	Just 8 articles about the potato leaf diseases classification results
Kumar et al. (2022)	2022	List the factors may produce plant disease	Did not list available public datasets
Bhagat (2022)	2022	Detailed pre-processing, feature extraction & classifier analyses	Did not list available public datasets
Raina and Gupta (2021)	2021	Concluded that multi-layer CNN performance is better than shallow ML	The number of papers they reviewed is relatively small (17 papers)
Ekanayake and Nawarathna (2021)	2021	Focused datasets, categories, DL methods and average accuracy	Most of papers worked on Plant Village, The number of papers was too small (10 papers)
Appalanaidu and Kumaravelan (2021)	2021	Detailed analysed 45 recent papers, pointed out the deficiency of SL compared to DL and feature extraction may be unnecessary to DL	Different accuracy from different datasets, there may be a lack of benchmark datasets
Li et al. (2021)	2021	Analysed the weaknesses of SL, affirmed the superiority of DL and introduced transfer learning. Besides, reviewed the common visualization techniques for explainability	Because of the lack of available data most of the models had poor robustness; only suitable for special species and leaves
Divya et al. (2021)	2021	Reviewed recent developments of DL (CNN, DNN and TL)	A few articles and studies in general
Agarwal et al. (2021)	2021	Some summaries of plant pathology	A few articles about Leaf disease classification and a small number of publicly available datasets
Metre and Sawarkar (2021)	2021	Detailed analyses of image segmentation, feature extraction and classification stages	Most of the work is about shallow ML
Nisar et al. (2020)	2020	Focused on disease recognition, analysed crop types, disease Types, test set percentages, common techniques and classification accuracy, and common techniques and their accuracy	Most of the papers are before 2017 and the focus is on detection tasks (disease/not disease)
Chouhan et al. (2020)	2020	Detailed analysed related PA concepts and technologies (esp. Colour Space Models & Feature Extraction) and introduced the common diseases	Most of the listed datasets are private and access unavailable

Table 2 (continued)

Paper	Year	Strength	Limitation
Lu and Young (2020)	2020	Analysed many publicly available datasets (15 weed control, 10 fruit classification and 9 others)	Only the Maize Leaf (NLB) Dataset is for leaf disease classification
Muresan et al. (2020)	2020	Reviewed 26 papers' datasets, methods & results and confirmed DL's efficiency	Did not list available public datasets

et al. (2021); Bhagat (2022). This dataset is useful for the scientific research purpose, however, there are some pitfalls due to its laboratory-condition. In, Kumar et al. (2022); Agarwal et al. (2021); Metre and Sawarkar (2022), the authors expressed the importance of real-field datasets. In another research, a combination of public (55% based on Plant Village) and private data (25%) is used Bhagat (2022). Recently, more calls on the availability of leaf disease data to bring greater benefits to both scientific and industrial communities Agarwal et al. (2021).

Third, there are many different machine-learning approaches, and they need to be reviewed thoroughly. Early survey studies focus on traditional (shallow) approaches such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), AdaBoost, KNN, Decision Tree, Naïve Bayes (NB) Raina and Gupta (2021); Nisar et al. (2020); Applalanaidu and Kumaravelan (2021); Bangari et al. (2022); Metre and Sawarkar (2021); Bhagat (2022). In these approaches, data pre-processing and feature engineering are usually needed Raina and Gupta (2021); Li et al. (2021); Nisar et al. (2020); Metre and Sawarkar (2021). Feature engineering is an important step to extract the features of images as inputs for ML models Applalanaidu and Kumaravelan (2021). Normally, hand-crafted features will be extracted which requires the involvement of humans, i.e. domain experts to define useful features. For feature extraction, there exists a wide range of methods, including Local Binary Patterns (LBPs) Histogram, Speeded Up Robust Features (SURF), Scale Invariant and Feature Transformation (SIFT), Gabor Energy Filtering, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Generalized Extreme Value (GEV) Distribution and Johnson SB Distribution Bhagat (2022).

Recent surveys have revolved around new techniques, including deep learning, such as, CNN Divya et al. (2021); Applalanaidu and Kumaravelan (2021); Bangari et al. (2022); Agarwal et al. (2021); Bhagat (2022), AlexNet, GoogLeNet, and VGGNet Applalanaidu and Kumaravelan (2021); Bangari et al. (2022); Bhagat (2022), Pooling Dilated CNNs Raina and Gupta (2021). Recently, traditional (shallow) approach has been replaced by deep learning methods Geetharamani and Pandian (2019), as it may cause side effects (Sharma et al. (2021); Bir et al. (2020)) due to human errors/biases during feature engineering step. A number of experimental results showed that DL is a powerful and useful way to detect and classify leaf diseases Mureşan et al. (2020); Li et al. (2021); Raina and Gupta (2021); Bangari et al. (2022); Divya et al. (2021); Applalanaidu and Kumaravelan (2021). DL technologies are relatively user-friendly, can extract image features and classify plant diseases automatically Li et al. (2021). For example, the higher accuracy of DL compared to the traditional (shallow) approach was demonstrated by Kumar et al. (2022). They found that DL models, with and without pre-training, achieved average accuracies of 99.64% and 98.64% respectively, surpassing the 95.71% accuracy of the traditional approach. For improvement, recent studies enhance the performance of machine learning models, especially deep learning, with supplementary techniques, such as segmentation Kumar et al. (2022); Metre and Sawarkar (2022); Bhagat (2022), data augmentation Li et al. (2021), and transfer learning Li et al. (2021); Divya et al. (2021); Agarwal et al. (2021), or combination of traditional and deep learning Applalanaidu and Kumaravelan (2021). Li et al. (2021) claimed that transfer learning would be the most effective method to boost the robustness of CNN classifiers. Applalanaidu and Kumaravelan (2021) employed a combination of different segmentation algorithms to extract better features of the images.

As we can see, each survey focuses on a different set of techniques and data based on various timelines. This makes it difficult to analyse and compare the research outcomes. Moreover, many software applications of ML for pathology, including leaf-disease analysis, have been developed recently and there is a lack of a review in this aspect. In this

paper, we will address the limitations above by providing a comprehensive review of recent studies, public datasets, machine learning techniques, and real-life applications of machine learning in leaf disease classification.

4 Datasets

Data plays a critical role in modern AI, especially in the emergence of deep learning techniques recently. The quantity and quality of training data will improve the performance of large models used in deep learning Goodfellow et al. (2016). In research and practice, the role of image datasets for computational vision tasks is self-evident. In Chouhan et al. (2020), a study showed that the foremost challenge for research is the lack of available datasets. For leaf disease classification, in recent years, many researchers have devoted themselves to the collection of plant disease data for public use. Table 3 and Fig. 2 show recent available public datasets about plant leaf diseases for computer vision research. In the table, the “Year” column represents the published year of a dataset. “Species” shows the number of plant species. The “Diseases” column lists the number of unique diseases. We also include a “Class” column to show the number of original classes in the dataset, as some datasets combine species and diseases as labels. We categorise the datasets into a multi-species group and a single-species group according to their species diversity.

4.1 Single-species datasets

A single-species dataset is specific to one plant species. It can be used in the detection, classification or severity assessment of a specialised plant.

4.1.1 Plant pathology 2021 - FGVC8 dataset

Plant Pathology 2021-FGVC8 is an apple leaf disease image dataset of a Kaggle challenge competition. It is a part of the Fine-Grained Visual Categorization FGVC8 workshop at the Computer Vision and Pattern Recognition Conference (CVPR) 2021. This dataset is characterised by each leaf having 1 or several labels. It contains around 23,000 apple images, and six apple leaf health categories: “healthy”, “complex”, “rust”, “frog eye leaf spot”, “powdery mildew”, and “scab”. Among them, “complex” means a leaf is unhealthy but we are unable to identify an exact cause (disease). This dataset would be useful for multi-class apple leaf disease classification.

4.1.2 Maize leaf (NLB) dataset

The Maize Leaf (NLB) Dataset was collected through various shooting methods proposed by Wiesner-Hanks et al. (2018). This includes hand cameras, cameras on a 5 m boom, and cameras on a drone. The dataset has more than 18, 222 maize plant images with 105, 735 Northern leaf blight (NLB) lesions annotated by experts. This dataset is considered as the largest open dataset of single plant species at present, and will be helpful for maize disease classification and severity assessment.

Table 3 Public leaf disease datasets

Dataset	Year	Species	Disease	Class	Link
Plant Village	2016	14	22	38	https://data.mendeley.com/datasets/tywbtsjrjv/1
plant leaves	2019	12	22	22	https://data.mendeley.com/datasets/hb74ynkjcjcn/1
Plantae_k	2019	8	9	16	https://data.mendeley.com/datasets/t6j2h22jpx/1
PlantDoc	2020	13	17	28	https://github.com/pratikakayal/PlantDoc-Dataset
Plant pathology 2021 - FGVC8	2021	1	6	6	https://www.kaggle.com/c/plant-pathology-2021-fgvc8/overview
Maize leaf (NLB)	2018	1	2	2	https://osf.io/p67rz/
Citrus leaves	2019	1	5	5	https://data.mendeley.com/datasets/3f83gxm57/2
Rice diseases image dataset	2019	1	4	4	https://www.kaggle.com/minhhuy2810/rice-diseases-image-dataset
JMuBEN Arabica coffee leaf images	2021	1	3	5	https://data.mendeley.com/datasets/t2r6rszp5c/1
JMuBEN2			2		https://data.mendeley.com/datasets/tgy3zb82nd/1
JMuBEN3 sweet potato leaf spot	2021	1	1	1	https://data.mendeley.com/datasets/jjn4ht687d/3
Cassava diseases	2019	1	5	5	https://www.kaggle.com/c/cassava-disease/data
UCI rice leaf diseases	2017	1	3	3	https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases

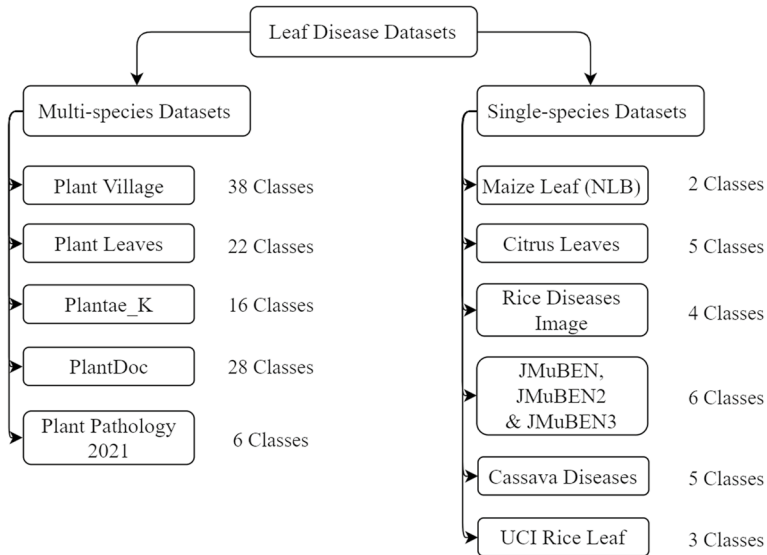


Fig. 2 The structure of public datasets

4.1.3 Citrus dataset

The Citrus dataset has two folders, 150 images of citrus fruits and 609 images of citrus Leaves, each folder has 5 categories (black spot, canker, greening, melanose, and healthy). All images were annotated by experts.

4.1.4 Rice diseases image dataset

Rice diseases image dataset has four categories of rice leaves: Brown Spot (523 images), Healthy (1488 images), Hispa (565 images) and Leaf Blast (779 images). The dataset has been studied in several works Kathiresan et al. (2021); Bifta Sama et al. (2021) for leaf disease classification.

4.1.5 JMuBEN datasets (JMuBEN, JMuBEN2, JMuBEN3)

This is a group of datasets (JMuBEN, JMuBEN2, JMuBEN3) that were released by the same authors Jepkoech et al. (2021) and were all collected by a camera under plant pathologists' guide. JMuBEN and JMuBEN2 are about Arabica coffee leaves that were taken from real coffee plantations. They can be combined into a larger dataset. JMuBEN has three categories: 7682 *Cercospora* images, 8337 rust images and 6572 *Phoma* images. JMuBEN2 has two categories: 16,979 *Miner* images and 18,985 healthy images. JMuBEN3 is about sweet potato leaves which are all affected by leaf rust. It just has one category: 1383 Sweet potato leaf rust images. The JMuBEN3 dataset folder also contains a sweet potato leaf rust classification model code by the authors. Some images of JMuBEN and JMuBEN2 were

augmented by rotation and flipping methods to increase dataset size and prevent the overfitting issues Jepkoech et al. (2021). These datasets are useful for deep learning research and study.

4.1.6 Cassava disease dataset

Cassava disease dataset is from a Kaggle challenge competition as a part of the Fine-Grained Visual Categorization workshop (FGVC6) at CVPR 2019. It contains 1 healthy and 4 disease categories which are Cassava Brown Streak Disease (CBSD), Cassava Mosaic Disease (CMD), Cassava Bacterial Blight (CBB) and Cassava Green Mite (CGM). All images were collected by 200 farmers through small phones and annotated the labels by experts. The dataset has two parts, one is a training set (9436 annotated images) and another is a test set (12,595 unlabeled images). In the dataset, the experts also scored the disease severity (from 1 to 5), however, the Kaggle did not include the scores Mwebaze et al. (2019).

4.1.7 UCI rice leaf diseases dataset

UCI Rice Leaf diseases dataset aims to use for rice plant diseases detection and classification Prajapati et al. (2017). It has three disease categories: Bacterial leaf blight, Brown spot, and Leaf smut, and each category has 40 images. The limitation of it is the size is too small (120 images total). This can be useful for prototyping machine learning methods for quick testing but may not be suitable for deep learning approaches which require large amounts of data.

4.2 Multi-species datasets

A multi-species dataset is composed of a variety of plant species, each has its own (overlapping) set of diseases. The datasets in this group can be used for the classification of species and classification of diseases.

4.2.1 Plant Village dataset

Plant Village Dataset is currently the most widely used and popular public dataset for leaf disease classification. It has two versions, an original version and a data augmentation version. The original dataset was published in 2016 by Hughes and Salathe (2016) with 54,305 leaf diseases or healthy images from 14 plant species (e.g., Apple, Blueberry, Cherry and Corn). Each species has 1–10 classes of related diseases or healthy (22 unique disease categories total). In the dataset folder, it has a total of 38 classes that combined species and diseases (e.g., Apple black rot), and one additional category of about 1143 background images (without leaf). The data augmentation version was released in 2019 by Hughes and Salathe (2015), they used six data augmentation methods (i.e. image flipping, Gamma correction, noise injection, PCA colour augmentation, rotation, and Scaling) to enhance the data. As a result, the original dataset had been increased from 54,305 to 61,486 images.

4.2.2 Plant leaves dataset

Plant Leaves dataset consists of 4502 images of healthy and unhealthy leaves divided into 22 categories by species and state of health. The images are in high-resolution JPG format. 12 tree types are *AlstoniaScholaris*, Arjun, Bael, Basil, Chinar, Gauva, Jamun, Jatropha, Lemon, Mango, Pomegranate, and *PongamiaPinnata*. Notice that the Bael class only has diseased leaves and Basil only has healthy leaves.

4.2.3 Plantae_K dataset

Plantae_K dataset contains 2153 images of healthy and unhealthy plant leaves, divided into 16 categories by species and state of health (e.g., apple healthy and apple diseased). The images are in high-resolution JPG format. There are 8 fruit types in this dataset, including Apple, Apricot, Cherry, Cranberry, Grapes, Peach, Pear and Walnut.

4.2.4 PlantDoc dataset

Compared to Plant Village Dataset, the PlantDoc dataset aims to establish a real-field images dataset. Singh et al. (2020a) concerned that the images of Plant Village (e.g., see Fig. 3a) were all taken in laboratory setups and not in the real conditions of cultivation fields. This would impact the trained model's efficacy and real-life applications. Based on that, they built the PlantDoc dataset, which can be a sufficiently large-scale non-lab dataset for leaf disease classification. The images in PlantDoc have cluttered backgrounds and are without a standard format. A comparison between Plant Village images and PlantDoc images can be seen in Fig. 3. PlantDoc has similar categories to Plant Village with 2598 leaf images from 13 plant species. In this dataset, there are 17 unique disease categories and 38 classes for the combination of species and diseases (e.g., Apple Scab Leaf). The images were annotated by experts.

Take-home messages

1. Maize Leaf (NLB) dataset is the largest public dataset while Plant Village is the most popular dataset.
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(a) Plant Village

(b) PlantDoc

Fig. 3 Apple scab leaf samples

Take-home messages

2. Plant Village, Plant Leaves and Plantae K are laboratory datasets which can be useful for prototyping and evaluating machine learning models. However, real-field datasets would provide a more comprehensive evaluation and support for realistic applications.
3. We found that the available datasets are very useful for domain-adaptation and multi-task learning, however, this is largely missing in the current literature. We would suggest a machine learning model to learn from different datasets in a compositional manner where the model can effectively adapt to new tasks/datasets added in.

5 Machine learning approaches

Generally, there are currently three general directions for machine learning approaches for leaf disease classification (see Fig. 4), including shallow learning (SL), deep learning (DL), and augmented learning (AL). In shallow learning approaches, leaf localisation always was done first, then based on the diseased leaves to classify the diseases. In addition, feature extraction is the necessary step of shallow learning to extract the features of leaves before classification. Deep learning has been emerging as a great tool for leaf disease classification recently thanks to its ability to offer an end-to-end process for learning and prediction. Deep learning does not require the feature engineering step and is able to learn an effective classifier from input images. At present, the advantages and disadvantages of shallow learning and deep learning approaches are still inconclusive. However, there is a strong agreement that SL has disadvantages in leaf image classification tasks, such as the inability to apply to large datasets, complex processing pipelines, and especially the need for feature extraction Applalanaidu and Kumaravelan (2021); Li et al. (2021). DL, however, also has two main disadvantages: computationally expensive and data-hungry. With the development of related hardware and computing systems, the computation expensiveness of DL has been alleviated. For the data hungriness issue, recent approaches employ augmented

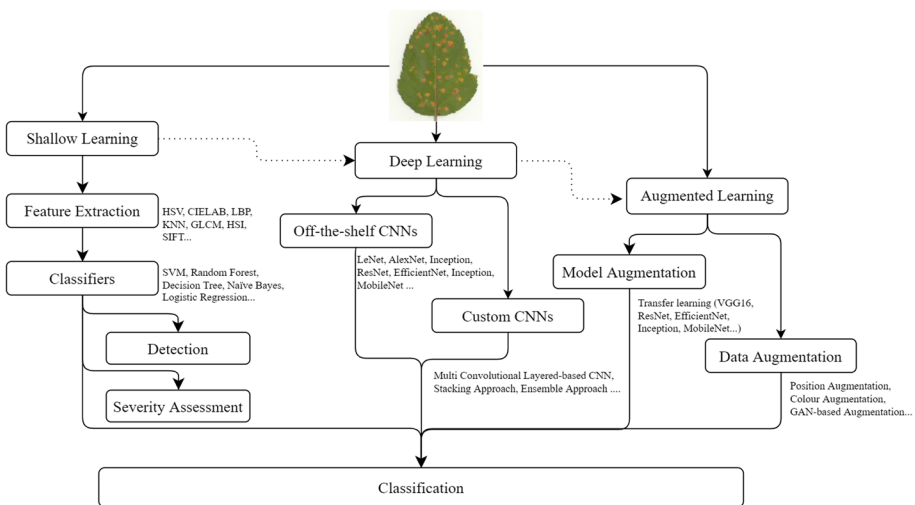


Fig. 4 ML development in leaf disease classification

learning techniques by generating artificial data and/or reusing pre-trained models from other domains/tasks.

5.1 Shallow learning

Table 4 summarises the details of this study through shallow machine learning approaches (if there is a comparison, the highest accuracy is in bold). We focus on the recent and notable papers from 2019. The general stages for leaf disease identification and classifications using shallow learning include: data(image) acquisition, processing, segmentation (possibly Metre and Sawarkar (2022, 2021)), feature extraction, and identification (or classification) Raina and Gupta (2021); Li et al. (2021); Metre and Sawarkar (2022, 2021). While data acquisition, processing, and segmentation are common in image processing generally, in this section we discuss two aspects that directly affect the quality of leaf disease classification.

5.1.1 Feature engineering

Normally, data was collected from digital cameras (sometimes specialised cameras are used) to obtain basic features in colour models, such as RGB Chaudhari and Patil (2020), HSV Kirti Rajpal (2020); Mukhopadhyay et al. (2021), and CIELAB Chaudhari and Patil (2020); Kirti Rajpal (2020). Among the three colour models, HSV is more popular than the others. For example, Chaudhari and Patil (2020) collected 618 images from farms in RGB format before being converted to CIELAB colour space and resized to 400×600 pixels. In Kirti Rajpal (2020), the authors used two colour models (HSV and CIELAB) for Plant Village data to perform the segmentation for feature extraction. Mukhopadhyay et al. (2021) collected 312 samples of tea leaves from three Indian tea gardens and convert them from RGB format to HSV for data pre-processing. From a colour model, we can extract more task-related features based on the spatial structure of the image data. The two most common methods for feature extraction are K-means clustering Kirti Rajpal (2020); Padol and Yadav (2016); Kumar et al. (2020); Chaudhari and Patil (2020) and grey-level co-occurrence matrix (GLCM) Bharate and Shirdhonkar (2020); Tulshan and Raul (2019); Dang-Ngoc et al. (2021); Kumar et al. (2020); Shahidur Harun Romy et al. (2021). From the literature, we found that GLCM features achieves better performance than K-Means features. Other extraction methods from image processing are employed as well. In Mukhopadhyay et al. (2021), the authors used Non-dominated Sorting Genetic Algorithm (NSGA-II) to detect the tea leaf's disease area and then applied Principal Component Analysis (PCA) to extract 5 most significant features for classification. In Singh et al. (2020b) features are extracted from RoI (Region of Interest) segmentation. In Das et al. (2020), Gaussian blur and Haralick's algorithm are applied to extract 60 texture features. A comparison of different feature extractors was presented in Gadade and Kirange (2020). In this study, 9 different feature extraction methods are used, including Colour Mean Pixel Value, Colour moments, Edge Feature extraction using the Pewit operator, Gabor features extraction, Histogram features extraction, Haar features, Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP). Among them, HOG features perform the best. Besides standard approaches in image processing, a novel feature extraction method based on Local Binary Patterns (LBP), dedicated to leaf diseases, was proposed in Barburiceanu et al. (2020). This paper claimed that compared to recent grayscale LBP-based approaches, the new feature extraction method improved accuracy, precision and recall significantly.

Table 4 Machine learning technologies

Paper	Year	Dataset	Categories	Size (training/test)	Feature extraction	Accuracy
Kirti Rajpal (2020)	2020	Plant Village (Part)	2	250/150	K-means	SVM (94.1%)
Barburiceanu et al. (2020)	2020	Plant Village (Grape)	4	70%/30%	LBP	SVM (97.76%)
Singh et al. (2020b)	2020	Plant Village (Part)	2	126/54	ROI	SVM (97.2%)
Das et al. (2020)	2020	Plant Village (Tomato)	8	60%/40%	GB	LR(67.3%), RF(70.05%) & SVM (87.6%)
Gadade and Kirange (2020)	2020	Plant Village (Tomato)	10	70%/30%	Colour Mean Pixel Value, Colour Moments, Prewitt operator, Gabor, Histogram Features, Haar, Histogram of Oriented Gradients (HOG) & Local Binary Patterns (LBP)	HOG (the best FE) with, LR (Acc: 46.93%, F1: 44.17%), KNN (Acc: 44.10%, F1: 44.10%), SVM (Acc: 48.77%, F1: 40.38%), Naïve Bayes (Acc: 25.88%, F1: 27.22%) & DT (Acc: 39.74%, F1: 39.66%)
Jaysaprakash and Balamurugan (2021)	2021	Plant Village (Tomato)	5	N/A	LBP & SIFT	SIFT & MLP (92.40%), SIFT & RF (91.20%), LBP & MLP (90.40%) & LBP & RF (89.30%)
Shahidur Harun Romy et al. (2021)	2021	Rice Leaves (Self)	2	420/80	Color Histogram, Hu Moments & GLCM	RF (97.50%), Naïve Bayes, DT, LR, KNN & SVM
Padol and Yadav (2016)	2016	Grape Leaves (Self)	2	110/27	K-means	SVM (88.89%)
Bharate and Shirdhonkar (2020)	2020	Grape Leaves (Self)	2	60/30	GLCM	SVM (90%) & KNN (96.66%)
Tulshan and Raul (2019)	2019	Leaves (Self)	2	55/20	GLCM	KNN (98.56%) & Linear SVM (97.6%)
Dang-Ngoc et al. (2021)	2021	Citrus Leaves (Self)	4	170/170	GLCM	SVM (91.76%)
Kumar et al. (2020b)	2020	Leaves (Self)	5	N/A	K-means & GLCM	SVM (Around 96%)
Chaudhari and Patil (2020)	2020	Banana Leaves (Self)	4	371/247	K-means	SVM (85%)
Mukhopadhyay et al. (2021)	2021	Tea Leaves (Self)	6	312 (4-fold)	PCA	SVM (83%)
Rajesh et al. (2020)	2020	Leaves (Self)	5	N/A	N/A	Decision Tree (96%)

Combination of features extracted from different techniques. Jayaprakash and Balamurugan (2021) pre-processed all tomato leaf images through the Gaussian filtering (GF) technique first. After that, they tried to combine two feature extractors which are local binary patterns (LBP) and Scale Invariant Feature Transform (SIFT)

5.1.2 Classifiers

SVM was the most common ML classifier to classify the leaf diseases Kirti Rajpal (2020); Barburiceanu et al. (2020); Singh et al. (2020); Das et al. (2020); Gadade and Kirange (2020); Shahidur Harun Romy et al. (2021); Padol and Yadav (2016); Bharate and Shirdhonkar (2020); Dang-Ngoc et al. (2021); Kumar et al. (2020); Chaudhari and Patil (2020); Mukhopadhyay et al. (2021). Padol and Yadav (2016) used Linear SVM to detect the grape leaf disease, achieving 88.98% accuracy. However, the linear kernel only works well if the data is linearly separated, which is not the case in many applications. In Kirti Rajpal (2020), a study compared three different kernels of SVM (Linear, Polynomial, RBF) on HSV and CIELAB features for Black rot disease classification in grape plant. The result showed that a SVM model with RBF Kernel gained the best accuracy of 94.1%. SVM was reported to be applied successfully to Banana leaf (85% average accuracy) Chaudhari and Patil (2020), tea leaves Mukhopadhyay et al. (2021) (83% average accuracy, 78% F1-score), grape vine disease (97.2% average accuracy) Singh et al. (2020b). A comparison between SVM and Logistic Regression has been studied in Das et al. (2020) for tomato leaf disease classification. The results showed that SVM significantly outperforms Logistic Regression (20% better accuracy) and Random Forest (17% better accuracy). In Gadade and Kirange (2020) a more comprehensive comparison has been carried out with 4 competitors (Linear Regression, KNN, SVM, Naïve Bayes and Decision Tree) using 9 different types of features. It also concluded that SVM performs the best on tomato leaf disease diagnosis and severity measurement. A new SVM model was proposed in Dang-Ngoc et al. (2021), known as hierarchical SVM, to detect citrus leaf diseases where hierarchical SVM achieved 91.76% accuracy in comparison to 88.24% from traditional SVMs.

Besides SVM, other classifiers can achieve high performance if suitable features are selected. For example, in a small private dataset, the performance of K-Nearest Neighbor (KNN) is 98.56%, which is better than 97.6% from SVM Tulshan and Raul (2019). In Bharate and Shirdhonkar (2020), KNN outperforms SVM when using GLCM features for grape leaf images, achieving 96.66% in comparison to 90% from the latter. For rice leaf disease classification Shahidur Harun Romy et al. (2021), six ML algorithms, including RF, Naïve Bayes, Decision Trees, Logistic Regression, KNN and SVM, are compared. The feature set is a combination of Color Histogram, Hu Moments shape features, and Haralick texture features, which enabled RF to achieve the best performance (97.50% accuracy) on an IoT device (Raspberry Pi). Jayaprakash and Balamurugan (2021) pre-processed all tomato leaf images through the Gaussian filtering (GF) technique firstly. After that, they tried to combine two feature extractors which are local binary patterns (LBP) and Scale Invariant Feature Transform (SIFT) with two ML classifiers which are multilayer perceptron (MLP) and random forest (RF) models to classifier the tomato diseases. They measured the accuracy results of each feature extractor with each classifier, which are SIFT & MLP 92.40%, SIFT & RF 91.20%, LBP & MLP 90.40% and LBP & RF 89.30%. Decision Tree is a simple classifier and can be useful for small datasets with a small number of classes Rajesh et al. (2020). Here, the paper shows that after relabelling the classes from

four diseases and 1 healthy label to be a binary class, containingg ‘healthy’ and ‘unhealthy’ labels, Decision Tree can achieve 96% accuracy.

Take-home messages

1. Shallow machine learning requires feature extraction from images Applalanaidu and Kumaravelan (2021) to be useful for the disease classification task. The two most common methods are K-means clustering and grey-level co-occurrence matrix (GLCM), in which GLCM is more recommended. A combination of features is also encouraged, as it can help improve performance.
 2. Support vector machine (SVM) was the most common ML method for leaf disease classification. It is very suitable for both smaller (more likely to be linear) or non-linear datasets Thet et al. (2020). Its better performance in comparison to other classifiers is evident in several studies. However, if suitable features are selected, KNN or RF can achieve better accuracy.
 3. For small datasets with a small set of disease classes, simple methods can achieve good results.
-

5.2 Deep learning

Deep learning is a rising branch of machine learning which consists of different architectures and associated learning algorithms. For leaf disease classification, most deep learning models and algorithms are based on neural networks with many number of hidden layers. We categorise deep learning approaches for this task into deep neural networks, convolutional neural networks for image classification, and convolutional neural networks for object detection& classification. Table 5 provides a summary of recent Deep Learning approaches for leaf disease classification (if there is a comparison, the highest accuracy is in bold).

5.2.1 Deep neural nets

Deep neural networks are neural networks with multiple hidden layers, one on top of another. Previously, training such deep structures is difficult due to the problem of gradient vanishing/exploding but current learning techniques can turn that cure into a blessing, thanks to the availability of big data and powerful computing resources. We can use deep neural nets as a classifier, similar to shallow learning approaches. In Jana et al. (2021), deep Belief networks (DBN) were studied, together with other variants of multi-layer feed-forward neural networks, for pepper leaf disease classification. The models were evaluated on two datasets. The first dataset is self-collected, consisting of 1500 images of healthy and diseased leaves. The other dataset contains 300 healthy and 35 diseased images from Plant Village. All samples are resized to 256×256 pixels. The features used in this study was Gray Level Co-occurrence Matrix (GLCM). The average accuracy and F1-score of DBN are 91.956% and 0.77546, respectively. The results are slightly better performance.

The employment of feature engineering in deep learning seems not useful, as deep models themselves are effective feature extractors. Instead of two stages (feature extraction + classification) deep convolutional neural networks (CNN) can learn discriminative features that are useful for classification in an end-to-end manner.

5.2.2 Image classification CNNs

CNN is a class of neural networks where spatial information from image structure are represented and learned through convolution operations. CNNs have been used largely

Table 5 Summary of deep learning approaches

Paper	Year	Dataset	Categories	Size (training/test)	Augmentation	Features	Accuracy
Huang et al. (2020)	2020	Grape leaves (self)	5	80%/20%	Yes	Ensemble Method	Vanilla CNN (98%), improved VGG-16 (99%), improved MobileNet (97%), improved AlexNet (97%) & Ensemble (100%)
Xie et al. (2020)	2020	Grape leaves (self)	4	4449 images	No	N/A	Faster R-CNN (81.1%)
Agarwal et al. (2020)	2020	Plant Village (Tomato)	10	10,000/7000/500 ^a	Yes	Assessed Storage Space	CNN (91.2%) , Mobilenet (63.75%), VGG-16 (77.2%)& InceptionV3 (63.4%)
Singh et al. (2020a)	2020	PlantDoc (cropped)	28	80%/20%	Yes	Created PlantDoc Dataset	VGG-16 (60.41%), InceptionV3 (62.06%) & InceptionResNet V2 (70.53%)
Thet et al. (2020)	2020	Grape leaves (self)	6	80%/20%	Yes	Global Average Pooling (GAP)	VGG-16 with GAP (98.4%)
Sardogan et al. (2018)	2018	Plant Village (tomato)	5	500(80%/20%)	No	with Learning Vector Quantization	CNN (86%)
Bhowmik et al. (2020)	2020	Tea leaves (self)	3	1000/270/30 ^a	Yes	N/A	CNN (95.93%)
Guan (2021)	2021	Plant Village (modified)	61	31718/4540	Yes	Stacking Method	Stacking Model (87%) , ResNet (82.78%), Inception-Net (82.22%), DenseNet (83.44%)& InceptionResNet (84.07%)
Iakshmi and Nickolas (2020)	2020	Betelvine leaves (self)	3	1014 images	No	Proposed Mask-RCNN (ResNet50 & Feature Pyramid Network)	F1: Proposed Mask-RCNN (84.07%) , Faster RCNN (74.32%) & Mask RCNN (83.11%)
Kawatra et al. (2020)	2020	Plant Village (whole)	38	N/A	Yes	Hybrid Approach: AlexNet + Linear SVM	Hybrid Model (99.98%) , Basic AlexNet (96.34%) & AlexNet with GAP Layer (97.29%)

Table 5 (continued)

Paper	Year	Dataset	Categories	Size (training/test)	Augmentation	Features	Accuracy
Chowdhury et al. (2021)	2021	Plant Village (tomato)	2, 6, 10	5-fold	Yes	N/A	EfficientNet B0, B4, B7 (97%–99%)
Surya and Gautama (2020)	2020	Cassava leaves Mwebaze et al. (2019)	5	5656/ 1889/ 1885 ^a	No	N/A	MobileNet (85.38%)
Sunil et al. (2020)	2020	Plant Village (peach, pepper & strawberry)	6	70%/50%	N/A	Tested different epochs (50, 75, 100 & 125)	Multi convolutional layered-based CNN (87.47%–99.25%)
Jana et al. (2021)	2021	Pepper leaves (self)	2	N/A	N/A	Used GLCM as Feature Extraction	DBN (91.956% & 77.546%) , FFNN (91.156% & 63.936%), BPNN (91.306% & 66.916%), DNN (91.386% & 67.246%), RNN (91.436% & 67.486%) & CNN (91.616% & 72.046%) ^b
Hu et al. (2021)	2021	Tea leaves (self)	3	318/80, 1400/200	Yes	Diseased Leaf classification & Disease Severity Analysis	Faster region-based CNN (91.22%)
Anandhakrishnan and Jaisakthi (2020)	2020	Plant Village (Tomato)	10	80%/20%	No	N/A	Xception V4 (99.45%) , AlexNet (90.1%), Lenet (88.3%), Resnet (98.40%) & VGG-16 (90.1%)
Zhang et al. (2018)	2018	Maize leaves (self & Plant Village)	9	80%/20%	Yes	N/A	Fine-tuned GoogLeNet (98.9%) & Cifar10 (98.8%)

^aTraining/validation/test amount

^b Acc & F1

in image processing and computer vision, especially in classifying images, and therefore have been useful for leaf disease classification as well.

5.2.2.1 Off-the-self CNNs There are a plethora of convolutional neural networks developed to tackle a wide range of problems in image classification. One can easily pick up a model and apply it to classify disease from leaf images.

5.2.2.2 LeNet and GoogLeNet LeNet Lecun et al. (1998) is one of the earliest convolution CNNs, although it does not have a very deep architecture, its convolution idea is the inspiration for many other deep CNNs models nowadays. In Kawatra et al. (2020), LeNet achieved the lowest accuracy (94.0%) compared to other approaches on Plant Village. A newer version, called GoogLeNet (also known as Inception V1), was developed with improvements from LeNet with several novel components added, such as batch normalization, image distortions, and more layers. In Vijaykanth Reddy and Sashi Rekha (2021) GoogLeNet achieved 95.69% accuracy and ranked 3rd in 7 CNN models for Apple disease classification. In Zhang et al. (2018) it achieved 98.9% accuracy for the classification of Maize leaf diseases.

5.2.2.3 AlexNet As one of the earliest deep CNN models, AlexNet has been employed in multiple studies of leaf disease classification Geetharamani and Pandian (2019); Ashok et al. (2020); Agarwal et al. (2019); Anandhakrishnan and Jaisakthi (2020); Huang et al. (2020); Kawatra et al. (2020). For tomato diseases, AlexNet achieved promising results, such as 95.75% accuracy in Ashok et al. (2020) and 90.1% accuracy Anandhakrishnan and Jaisakthi (2020) (they used different testing partitions). AlexNet was also reported to have 86.5% accuracy for grape diseases in Agarwal et al. (2019). Although AlexNet was a popular model, its performance was usually inferior compared to other deep CNNs. For improvement, Kawatra et al. (2020) proposed a hybrid approach by combining AlexNet and Linear SVM to boost the accuracy to 99.98% on the Plant Village dataset. This is significantly better than AlexNet alone (94.3%), ResNet50 (98.06%), VGG-16 (98.76%), and Inception V3 (99.08%).

5.2.2.4 VGG Very Deep Convolutional Networks, known as VGG or VGGNet, is an idea of how to effectively increase the depth of CNNs. VGG-16 (VGG with 16 layers) has been applied to tomato leaves datasets Agarwal et al. (2020); Anandhakrishnan and Jaisakthi (2020). In Agarwal et al. (2020) a pre-trained model was used to achieve 77.2%. In Anandhakrishnan and Jaisakthi (2020) a better training approach was proposed where the performance was much higher with 90.1% accuracy. A deeper version of VGG, VGG-19, was employed in Bir et al. (2020) to successfully classify tomato leaf diseases with 96.86% accuracy. In Hu et al. (2021) used VGG-16 to do the severity analysis The proposed model gained 91.22% Accuracy. Sujatha et al. (2021) applied VGG-16 and VGG-19 on a citrus leaf disease dataset. Notably, VGG-16 has been applied widely to grape leaf images Agarwal et al. (2019); Huang et al. (2020); Thet et al. (2020). Thet et al. (2020) tested VGG-16 on their private grape leaf diseases dataset (5 leaf diseases and 1 healthy category, 6000 images). Some modifications of VGG16 have been developed by replacing two last two fully connected layers with the Global Average Pooling layer. The results showed that the proposed has the best accuracy (98.4%), significantly better than normal VGG-16 and the combination of VGG-16 and SVM classifier.

5.2.2.5 Inception Inception is a class of CNNs that utilises Inception modules for deeper structure with more efficient computation. In leaf disease classification, Inception V3 was the most popular among different versions of Inception networks. It was employed for tomato leaf diseases Agarwal et al. (2020). In Krishnamoorthy and Parameswari (2021) Inception V3 achieved 95.41% on a rice diseases image dataset, better than VGG-16 and ResNet-50. For the benchmark Plant Village dataset, InceptionV3 was reported to receive 98.42% Hassan et al. (2021), and **99.74%**, Sai (2021). Again, they have different results because of the different partitions for training, validation, and test.

5.2.2.6 ResNet Among many deep CNN models, ResNet is a powerful structure where we can train the model with a lot of layers to gain performance superiority. ResNet-50 achieved 98.40% accuracy for tomato leaves Anandhakrishnan and Jaisakthi (2020). Guan (2021) applied ResNet to achieve 82.78% in modified Plant Village. For Betelvine leaf disease, Kumar et al. (2020a) showed that ResNet-34 outperformed other models with 99.40% accuracy & 0.9651 F1-score. These are much better than SVM (50.69% & 50.57%), Decision Tree (72.23% & 72.02%), Logistic Regression (80.99% & 80.88%) and K-NN (87.86% & 88.06%). Another version, ResNet-20, achieved 92.76% on apple leaf images Vijaykanth Reddy and Sashi Rekha (2021). Recent works integrate the idea of residual blocks in ResNet and Inception module Hassan et al. (2021) to create InceptionResNetV2. Such a combination increases the performance from 98.42% to 99.11% on the Plant Village dataset.

5.2.2.7 MobileNet and EfficientNet Besides very deep models as we discussed above, some compact architectures were also employed, thanks to the increasing demand for IoT and hardware devices in plant pathology. For example, MobileNet can predict grape leaf diseases with 86% accuracy Huang et al. (2020). In Surya and Gautama (2020), MobileNet was applied to predict diseases from Cassava leaves Mwebaze et al. (2019). This public dataset has 1 healthy and 5 disease classes and was split into a training set (5656 images), a validation set (1889 images) and a test set (1885 images). All images are resized to 224×224 pixels. The proposed MobileNet model gained 85.38% accuracy. In Agarwal et al. (2020) MobileNet was shown to achieve 63.75% on tomato leaf images. In Chowdhury et al. (2021), the authors employed three sub-models (B0, B4, B7) of EfficientNet to classify tomato leaf diseases (Plant Village's 10 tomato categories). There are three types of this study's classification tasks, binary classification (healthy or unhealthy), six-class classification (1 healthy and 9 diseased categories are categorized into 5 classes, i.e., bacterial, fungal, viral, mold, and mite disease) and ten-class classification (1 healthy and 9 diseased). All images were resized to 224×224 and data augmentation was applied. The evaluation was carried out with 5-fold cross-validation. The results showed that for binary classification and six-class classification, EfficientNet-B7 had the best performance with an accuracy of 99.95% and 99.12%, respectively. For the ten-class classification, EfficientNet-B4 performed better than other models with an accuracy of 99.89%.

5.2.2.8 Custom CNN Although off-the-shelf CNN models were shown to be useful for leaf disease classification, they were originally designed and tested for general image classification tasks using benchmarking datasets, much different from leaf images. Therefore, they may not be optimal for this specific task and custom CNN models can be best for each dataset. Many researchers customised and developed their own CNN models, either from scratch or modify from existing ones. In Agarwal et al. (2020), a new CNN model was developed to classify tomato leaf diseases (extracted from Plant Village). They compared the proposed

CNN model with Mobilenet, VGG-16 and InceptionV3. The proposed model's accuracy is 91.2%, better than the others, and its storage space is the smallest (1696 KB). Sardogan et al. (2018) also studied tomato leaves from Plant Village. They used the CNN model with Learning Vector Quantization (LVQ) algorithm to classify the diseases. The model achieved 86% average accuracy. Another variant of CNNs was proposed in Bhowmik et al. (2020) to classify two tea leaf diseases. The precision of this model was approximately 95.93%. In Sunil et al. (2020), the authors designed a new Multi Convolutional Layered-based CNN model and apply it to three sub-datasets (Peach, Pepper, and Strawberry) from Plant Village. They showed that their CNN can effectively classify the leaves of three sub-datasets with accuracy from 87.47% to 99.25%. The CNN model in Anandhakrishnan and Jaisakthi (2020) was developed based on Xception V4 architecture and was tested to compare with several common pre-trained models, including VGG-16, ResNet-50, AlexNet and LeNet. The dataset used in this study is 10 classes of tomato leaves from Plant Village, where 14528 images were split into 80% for training and 20% for testing. The experiment results (in accuracy score) are: the proposed model (99.45%), AlexNet (90.1%), Lenet (88.3%), Resnet (98.40%) and VGG-16 (90.1%). Huang et al. (2020) tested Vanilla CNN and three pre-trained models (VGG-16, MobileNet & AlexNet). Finally, they built an ensemble model (average voting method) which achieve perfect accuracy of 100%.

A stacking approach was developed in Guan (2021), aiming to create an effective way to improve classification accuracy. The dataset in this work is from AI-Challenger 2018 (which was modified from Plant Village), it contains 10 different plant species and 61 classes. They split the dataset into a training set (31718 images) and a test set (4540 images). After data augmentation, the training set has been trained by four models (Inception Network, ResNet, Inception Combine ResNet and DenseNet), and being stacked. The stacking method achieved 87% accuracy, better than ResNet (82.78%), Inception Net (82.22%), DenseNet (83.44%) and Inception-ResNet (84.07%).

Another idea is to employ a hybrid approach, between deep learning and shallow learning, where deep learning would play a role of a feature extractor Kawatra et al. (2020). In this work, AlexNet was combined with Linear SVM to classify diseases in the Plant Village dataset (resized to 227×227 pixels). The experimental results showed that their proposed model gained 99.98% accuracy better than the basic AlexNet (96.34%) and AlexNet with Global Average Pooling Layer (97.29%). In addition, they evaluated different optimizers (AdaMax, AdaDelta, Adam, RMS Prop, SGD, AdaGrad) and showed that AdaMax has the best performance in this study.

5.2.3 Object detection and classification CNNs

In real-life scenarios, it would be useful if a system can detect leaves from cluttered backgrounds and classify their diseases. In this case, image segmentation can be applied as a first stage to extract the leaves area before applying CNNs for image classification as we discussed in the previous section. However, it would be more convenient to have an end-to-end approach where CNNs can detect leaves and identify diseases. In Xie et al. (2020), the authors employed a Faster Region-based CNN (R-CNN) model to detect and classify grape leaf disease with the best accuracy of 81.1%. Faster R-CNN was also the interesting model in Singh et al. (2020a) for an evaluation of the PlantDoc dataset. They claimed that fine-tuning Faster R-CNN with InceptionResnetV2 and MobileNet can reduce the classification error significantly. Hu et al. (2021) proposed a model based on Faster R-CNN to detect tea leaf blight (TLB) and used VGG-16 to do the severity analysis. The dataset of disease

classification has 398 images. Among them, 80 made up the test set. The dataset of severity analysis contains 270 mildly diseased leaf images (after augmentation, it increased to 700) in the training set and 100 in the test set, 700 Severe diseased leaf images in the training set and 100 in the test set. The proposed model gained 91.22% accuracy. lakshmi and Nickolas (2020) studied another variant of R-CNN, namely Mask R-CNN. They improved Masked-RCNN with ResNet50 and Feature Pyramid Network as key components, to classify Betelvine leaf diseases. For evaluation, a private dataset was collected from real cultivated Betelvine crops containing two diseases which are Anthracnose (358 images) and *Phytophthora* (456 images), and 1 healthy category (200 images). All images are resized to 256×256 pixels. The proposed Mask-RCNN model achieved 84.07% F1-score, which is better than Faster-RCNN (74.32%) and the original Mask-RCNN (83.11%).

5.2.4 Comparison between DL and SL

Early applications of deep learning attempted to integrate deep models with feature extraction. For example, in Ramya et al. (2021) and Ashok et al. (2020), the authors employed hand-crafted features for image segmentation before training CNNs to classify the tomato leaf diseases. In particular, Ramya et al. (2021) employed k-means clustering for feature extraction, coupled with CNNs to estimate disease severity, although their results are not clearly detailed. In Ashok et al. (2020) Discrete Wavelet Transform (DWT) and grey-level co-occurrence matrix (GLCM) features were used to segment leaves from the background which helped a CNN model to achieve 98.12% accuracy, better than AlexNet (95.75%) and traditional (shallow) neural networks (92.94%).

Comparisons between SL and DL methods have been carried out largely in recent years. When applying them on the same datasets the performance of DL methods tends to be superior. Deep learning approaches, such as CNNs, are very effective in image classification where abundant data is available as CNNs can extract discriminative features from images automatically. Therefore, the descriptiveness of feature extractors used in shallow learning can be a bottleneck for classifying leave diseases from images. We show the details of the current comparison in Table 6 (if there is a comparison, the highest accuracy is in bold). Sujatha et al. (2021) compared the performance of SVM, RF, Stochastic Gradient Descent (SGD), Inception-V3, VGG-16 and VGG-19 on the citrus leaf disease dataset. Using 10-fold cross-validation, 3 deep learning methods were shown better than the shallow counterpart. A study in Sharma et al. (2020) compared logistic regression(LR), KNN, and SVM with CNN on the Plant village dataset. The shallow learning methods in this work used K-means clustering as the feature extractor. The experimental results demonstrated that CNN got an overwhelming victory (98% accuracy) compared to other ML methods (around 60%). A deeper study has been shown in Saraswathi et al. (2021) where the authors analysed the weaknesses of several shallow learning methods, including K-Means, (shallow) artificial neural networks (ANN), Naïve Bayes, SVM, and KNN. For the empirical results, K-Means and ANN have quite low accuracy, and Naïve Bayes has a slow convergence rate. Meanwhile, SVM achieves relatively poor performance and KNN has some dimensionality issues. The such analysis led to an investigation into a system based on CNNs to improve the performance. As expected, the proposed CNN achieved the best accuracy (96%). Agarwal et al. (2019) used general data augmentation methods i.e. zooming, inversion, flipping, rotation, to make the training free from bias for any particular class (a.k.a balancing data). In this work, the CNN model also achieved the best accuracy of 99%. This is better than other pre-trained models they tested (AlexNet:

Table 6 Comparison between ML & DL

Paper	Year	Dataset	Categories	Size (training/test)	Feature extraction	Accuracy
Sharma et al. (2020)	2020	Plant Village (Whole)	19	N/A	K-means	LR (66.4%), KNN (54.5%) & SVM (53.4%) CNN (98%)
Saraswathi et al. (2021)	2021	Plant Village (part)	15	80%/20%	None Co-occurrence Matrix	CNN (96%) , ANN (90%), KNN (88.6%), SVM (85%), Naïve Bayes (79.6%) & K-means (72.3%)
Ramya et al. (2021)	2021	Plant Village (tomato)	N/A	N/A	K-means & GLCM	CNN (N/A)
Agarwal et al. (2019)	2019	Plant Village (grape)	4	3800/200	HSV-histogram	Decision Tree (80.5%), Naive Bayes (69.5%), SVM (85%), LDA (80.5%), KNN (96%), LR (94%), RF (97.5%), ANN (87.5%)
Geetharamani and Pandian (2019)	2019	Plant Village (whole)	38	55,636/1950	N/A	CNN (99%) , AlexNet (86.5%), VGG-16 (97.5%)
Kumar et al. (2020a)	2020	Plant Village (modified)	38	15,200 (80%/20%)	GLCM	SVM (50.69%), Decision Tree (72.24%), LR (81.00%) & K-NN (87.87%) CNN (97.87%) , AlexNet (87.34%), ResNet (92.56%), VGG-16 (92.87%) & Inception-v3 (94.32%)
Vijaykanth Reddy and Sashi Rekha (2021)	2021	Plant Village (apple)	4	10888/2801	None N/A	SVM (50.69% & 50.57%), DT (72.23% & 72.02%), LR (80.99% & 80.88%) & K-NN (87.86% & 88.06%) ResNet34 (99.40% & 96.51%)^a SVM (68.73%) & BP (54.63%)
Ashok et al. (2020)	2020	Tomato Leaves (self)	4	N/A	N/A	CNN (97.62%) , AlexNet (91.19%), GoogLeNet (95.69%), ResNet-20 (92.76%) & VGG-16 (96.32%)
Sujatha et al. (2021)	2021	Citrus Leaves Rauf et al. (2019)	5	10-fold	N/A	CNN (98.12%) , AlexNet (95.75%) & ANN (92.94%) RF (76.8%), SGD (86.5%) & SVM (87%)

Table 6 (continued)

Paper	Year	Dataset	Categories	Size (training/test)	Feature extraction	Accuracy
					None	VGG-19 (87.4%), inception-v3 (89%) & VGG-16 (89.5%)

^a Acc & F1

86.5%, VGG-16: 97.5%), and also other shallow learning approaches (Decision Tree, Naive Bayes, SVM, LDA, KNN, LR and RF). Among the shallow learning models, RF with HSV-histogram feature achieved the best result (97.5%). The proposed CNN model in Geetharamani and Pandian (2019) can classify leaf diseases with 97.87% accuracy, better than the popular transfer learning approaches (AlexNet, VGG-16, Inception-v3 and ResNet) and shallow learning approaches (SVM, logistic regression, decision tree and K-NN). In another work Kumar et al. (2020a), the authors employed Residual Networks (ResNet34) to construct a custom model with 99.40% accuracy and 96.51% F1-score. This results significantly surpass shallow learning models: SVM (50.69% & 50.57%), Decision Tree (72.23% & 72.02%), Logistic Regression (80.99% & 80.88%) and K-NN (87.86% & 88.06%). Vijaykanth Reddy and Sashi Rekha (2021) used their proposed approach (integrating CNN with AlexNet and GoogleNet cascade inception) to classify apple leaf diseases. Their proposed model gained 97.62% better than shallow learning, including SVM (68.73%) and Back Propagation (54.63%).

From multiple studies on the comparison between shallow learning and deep learning, some researchers concluded that compared with the shallow learning approaches the deep learning approaches, based on CNN architecture, can be more suitable and effective for leaf disease classification Sharma et al. (2020). As we can see, CNNs do not require manual pre-processing or feature extraction which may cause side effects Sharma et al. (2021); Bir et al. (2020), although it can shorten the training time and fewer computations for shallow learning. Table 6 clearly shows that CNNs outperform shallow learning by a significant margin. However, if the data is small, shallow learning can be more useful Zhang et al. (2018). In order to make deep learning effective, the quantity of data should be sufficient. In the next section, we will show how augmentation has been emerging as a great tool to deal with the data availability problem.

Take-home messages

- Deep learning models are useful for leaf disease classification and should be recommended in real-life applications due to their high accuracy. The common off-the-shelf deep learning models are CNN, AlexNet, VGG-16, ResNet, EfficientNet, Inception and MobileNet.
 - Custom CNNs are highly encouraged as we should design an optimal model for different tasks. It was evident that custom CNNs perform better than off-the-shelf models.
 - Deep learning is more effective than shallow learning in leaf disease classification. It is also more convenient as we can get rid of the feature extraction steps and minimise the manual effort for data processing.
 - Compare with Table 4, we can see that the datasets used in deep learning papers were relatively larger than in other studies. This is consistent with the fact that deep learning models are usually data-hungry.
 - Most of the studies focus on the performance (accuracy) aspect of the task while a more comprehensive comparison with compactness and efficiency is still missing. There are a few papers that addressed these issues, for example, Sharma et al. (2020) evaluates models' speed and Agarwal et al. (2020) evaluates models' storage space.
 - Different studies use different experiment settings, including different partitions for training/validation/test which makes their results difficult to compare. Therefore, a benchmarking study is needed.
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5.3 Augmented learning

5.3.1 Data augmentation

As mentioned previously, the main obstacle to this research is the availability of datasets Chouhan et al. (2020); Kumar et al. (2022); Li et al. (2021); Agarwal et al. (2021). More often situations researchers need to deal with the problem of not having enough data (i.e., small datasets) first, therefore, data augmentation is an effective method to solve this problem. Data augmentation can be seen as the imagination or dreaming of humans where we can simulate different scenarios based on our experience to anticipate unobserved events Shorten and Khoshgoftaar (2019).

Many research results have already confirmed the effectiveness of data augmentation in leaf disease classification Geetharamani and Pandian (2019); Mureşan et al. (2020); Naik et al. (2022); Shaji and Hemalatha (2022); Lamba et al. (2022); Nagaraju et al. (2022). Table 7 shows the common data augmentation methods in leaf disease classification. Data augmentation has several purposes, as follows: (i) enrich a dataset by increasing its volume Guan (2021); Moyazzoma et al. (2021); (ii) mitigate the data imbalance problem Li et al. (2021); Hu et al. (2021); (iii) improve the generality to reduce the over-fitting issue and make machine learning models more robust Guan (2021); Moyazzoma et al. (2021); Mureşan et al. (2020); Nagaraju et al. (2022). Generally, in leaf disease classification the common data augmentation approaches (including physical expansion Li et al. (2021) and position and colour augmentation Naik et al. (2022)), are widely used thanks to their convenience and simplicity. There are many existing functions and tools available for position augmentation, such as Pytorch's transforms function (`torchvision.transforms`) Kaushik et al. (2020) and the Augmentor python library Agarwal et al. (2020). Position augmentation methods mean changing the image's position, shape, size and so on. Rotating (rotation) is the most used method, as can be seen in Geetharamani and Pandian (2019); Agarwal et al. (2019); Huang et al. (2020); Zhang et al. (2018); Moyazzoma et al. (2021); Paymode et al. (2021); Chowdhury et al. (2021); Saraswathi et al. (2021); Kaushik et al. (2020); Agarwal et al. (2020); Jepkoech et al. (2021); Bir et al. (2020); Hu et al. (2021); Naik et al. (2022); Shaji and Hemalatha (2022); Lamba et al. (2022); Bhujel et al. (2022). Here, the method rotates leaf images to different angles (e.g. 30°, 90° or 180°) to produce new samples. After rotating, we can apply other techniques to generate more samples, such as flipping Geetharamani and Pandian (2019); Agarwal et al. (2019); Huang et al. (2020); Moyazzoma et al. (2021); Paymode et al. (2021); Saraswathi et al. (2021); Kaushik et al. (2020); Agarwal et al. (2020); Jepkoech et al. (2021); Bir et al. (2020); Naik et al. (2022); Shaji and Hemalatha (2022); Lamba et al. (2022); Bhujel et al. (2022), zooming/scaling Agarwal et al. (2019); Huang et al. (2020); Bir et al. (2020); Lamba et al. (2022); Bhujel et al. (2022); Geetharamani and Pandian (2019); Zhang et al. (2018); Chowdhury et al. (2021); Kaushik et al. (2020); Naik et al. (2022), cropping Paymode et al. (2021); Saraswathi et al. (2021); Agarwal et al. (2020); Naik et al. (2022), vertical or horizontal shearing Bhujel et al. (2022); Huang et al. (2020); Saraswathi et al. (2021), shifting Huang et al. (2020); Saraswathi et al. (2021); Bir et al. (2020); Shaji and Hemalatha (2022); Bhujel et al. (2022), transformation Paymode et al. (2021); Kaushik et al. (2020); Hu et al. (2021); Naik et al. (2022), translation Moyazzoma et al. (2021); Chowdhury et al. (2021); Kaushik et al. (2020); Naik et al. (2022); and resizing Kaushik et al. (2020); Agarwal et al. (2020).

Besides texture augmentation, researchers also used colour augmentation to process the leaf images, such as Brightness, contrast, saturation, hue Naik et al. (2022); Paymode et al.

Table 7 Common data augmentation technologies in leaf disease classification

Paper	Year	Datasets	Augmentation	Others
Geetharamani and Pandian (2019)	2019	Plant Village (Whole)	Image flipping, gamma correction, noise injection, PCA colour augmentation, rotation and scaling	Increase the performance
Agarwal et al. (2019)	2019	Plant Village (Grape)	Zooming, inversion, flipping and rotation	
Huang et al. (2020)	2020	Grape Leaves (Self)	Rotating, shift, shear, zoom and horizontally flip	
Zhang et al. (2018)	2018	Maize Leaves (Self and Plant Village)	Rotating, cutting and grayscale	
Moyazzoma et al. (2021)	2021	Leaves (Self)	Flipping, rotation, translation, channel drop	
Paymode et al. (2021)	2021	Plant Village (Tomato)	Cropping, flipping, rotating, transformation, noise rejection, colour augmentation	
Arun Pandian et al. (2019)	2019	Plant Village (Whole)	Neural style transfer (NST) and Generative Adversarial Networks (GANs)	
Chowdhury et al. (2021)	2021	Plant Village (Tomato)	Rotating, scaling, and translation	
Saraswathi et al. (2021)	2021	Plant Village (Part)	Rotating, shifting, flipping, cropping, and shearing	
Kaushik et al. (2020)	2020	Plant Village (Tomato)	Random Rotation, Random Resized Crop, and Random Rotation and Resized Crop	torchvision.transforms (Pytorch)
Agarwal et al. (2020)	2020	Plant Village (Tomato)	Rotating, flipping, cropping and resizing	Augmentor Package (python)
Jepkoech et al. (2021)	2021	JMuBEN and JMuBEN2	Rotating and flipping	
Bir et al. (2020)	2020	Plant Village (Tomato)	Rotating, vertical and horizontal flips, linear shifting and brightness & zoom variation	
Li et al. (2021)	2021	N/A	Generate Adversarial Networks (GANs)	
Hu et al. (2021)	2021	Tea Leaves (Self)	symmetrical transformation and rotating	
Naik et al. (2022)	2022	N/A	Position augmentation: Scaling, cropping, flipping, padding, rotation, translation and affine transformation	
			Colour Augmentation: Brightness, contrast, saturation and hue	

Table 7 (continued)

Paper	Year	Datasets	Augmentation	Others
Shaji and Hemalatha (2022)	2022	Plant Village (Whole)	Image blur, sharpening, contrast enhancement, shifting, rotation and flipping	Accuracy was raised from 97.59% to 99.5%
Lamba et al. (2022)	2022	N/A	Horizontal flipping, rotating, zooming and GANs augmentation	Increase images from 3941 to 9101
Nagaraju et al. (2022)	2021	Plant Village (Whole)	IPTA & IMHSA	Accuracy was raised from 65% to 73%
Raja et al. (2022)	2022	Plant Village (Apple and Grape)	Picture editing, changing over and upgrade	
Bhujel et al. (2022)	2022	Plant Village (Tomato)	Image zooming, vertical shearing, horizontal shearing, vertical flip, horizontal flip, vertical shift, horizontal shift & rotating	

(2021), and Principal Component Analysis (PCA) colour augmentation Geetharamani and Pandian (2019). It is worth noting that there may be pitfalls to the use of colour augmentation techniques for leaf images as colour is important to identify diseases. Therefore, we should be careful not to destroy or alter the original features of the leaf images. For example, some researchers used colour augmentation methods to change colourful leaf images Zhang et al. (2018); Naik et al. (2022); Geetharamani and Pandian (2019), but in Li et al. (2021) the authors pointed out that colour may be one of the most important manifestations of some leaf diseases, so changing the colour features of original images may bring negative effects.

The augmentation methods mentioned above may have limitations such as poor quality, inadequate diversity, and unevenness Li et al. (2021). Recent approaches, including Generative Adversarial Networks (GAN) Goodfellow et al. (2014), employ deep learning to generate artificial data. GAN techniques employ a neural networks called generator to produce images which are different from a training set to fool a classifier (a discriminator) as if they belong to some classes of the set. In the case of leaf images, GAN can generate new images for different disease types. Compared to the non-learning methods, GAN-based Data Augmentation is based on generative modelling and learning where the focus is on creating artificial samples and retaining similar characteristics from the original dataset. GAN has been widely used to create more samples recently Li et al. (2021). In Lamba et al. (2022), the original dataset comprises a total of 3941 images, including 1858 images of bacterial blight and 1706 images of leaf blast. After applying GAN augmentation, the dataset size increased to 9101 images, with 3767 images representing bacterial blight and 5034 images representing leaf blast, and the experimental results showed that the accuracy of CNN models can be improved with data generated from GAN.

Besides the texture/colour-based transformation and GAN approaches, there are some new methods were developed. For example, Nagaraju et al. (2022) proposed two image augmentation (IA) methods, including image pre-processing & transformation algorithm (IPTA) and image masking & REC-based hybrid segmentation algorithm (IMHSA). The methods aim to produce a sufficient quantity of training leaf disease images to improve the richness of small datasets. IPTA is an adaptive supervised learning approach to transform the original images into augmented images. IMHSA is an unsupervised approach for RGB image segmentation. The empirical study showed that with augmented data the validation accuracy was raised from 65% to 73%.

5.3.2 Model augmentation (transfer learning)

Transfer Learning (TL) is a technique in machine learning that allows models trained on one task to be adapted to perform another task. It also is a method to augment a learning model by reusing the knowledge learned from other domains for different (but related tasks). This could be useful in leaf disease classification, as models trained on one type of plant could potentially be adapted to work on other plants. There are many related works in this direction, including domain adaptation and multi-task learning, however, in most practice, we can employ pre-trained models which are firstly trained from a huge, public dataset (e.g., ImageNet dataset) for other tasks, then deploy them on the target leaf disease dataset (e.g., Plant Village). In Nagaraju et al. (2020), the authors showed that through transfer learning the training time of CNN models can be shortened significantly. This idea has been deployed and studied widely in leaf disease classification. Table 8 lists the recent

Table 8 Transfer learning

Paper	Year	Dataset	Augmentation	Pre-train	Accuracy
Nagaraju et al. (2020)	2020	Apple and Grape Leaves (Self)	No	ImageNet	Fine-tuned VGG-16 (97.87%)
Lauguico et al. (2020)	2020	Plant Village (Grape)	No	N/A	AlexNet (95.65%) , GoogLeNet (92.29%) & ResNet-18 (89.49%)
Moyazzoma et al. (2021)	2021	Leaves (Self)	Yes	N/A	Mobilnetv2 (90.38%)
Krishnamoorthy and Parameswari (2021)	2021	Rice diseases image dataset ^a	Yes	ImageNet	VGG-16 (87.08%), ResNet50 (93.41%) & InceptionV3 (95.41%)
Kibriya et al. (2021)	2021	Plant Village (Tomato)	No	ImageNet	VGG-16 (98.00%) & GoogLeNet (99.23%)
Meeradevi et al. (2020)	2020	Plant Village (Tomato)	No	ImageNet	Base VGG-16 (63.53%), Pre-trained VGG-16 (77.65%) & VGG-16 with L2 Regularisation (72.94%)
Sharma et al. (2021)	2021	Plant Village (Part)	No	ImageNet	F1-score: ResNet-50 with GAP & DCT Compression (92%), ResNet-50 with GAP (98%)
Kaushik et al. (2020)	2020	Plant Village (Tomato)	Yes	ImageNet	ResNet-50 (97%)
Bir et al. (2020)	2020	Plant Village (Tomato)	Yes	ImageNet	Segmented: CNN (83.46%), MobileNetV2 (96%), EfficientNet-B0 (96.40%) , VGG-19 (92.06%), Unsegmented: CNN (81.46%), MobileNetV2 (97.26%), EfficientNet-B0 (98.6%) , VGG-19 (96.86%)
Hassan et al. (2021)	2021	Plant Village (Whole)	No	ImageNet	InceptionV3 (98.42%), InceptionResNetV2 (99.11%), MobileNetV2 (97.02%) & EfficientNetB0 (99.56%)
Sai (2021)	2021	Plant Village (Part)	No	ImageNet	MobileNet (99.62%) & InceptionV3 (99.74%)

^aSee Table 3

work about transfer learning methods in leaf disease classification (if there is a comparison, the highest accuracy is in bold).

A study in Bir et al. (2020) adopted several pre-trained deep learning models, including MobileNetV2, EfficientNetB0 and VGG-19, to classify tomato leaf diseases (1 healthy and 9 diseased classes). From the experimental results (MobileNetV2: 97.26% accuracy, EfficientNet-B0: 98.6% accuracy, VGG-19: 96.86% accuracy), they claimed that transfer learning has several advantages: smaller size models, less computational costs, and suitable on the mobile devices. In Nagaraju et al. (2020), the authors utilised a pre-trained VGG-16 and fine-tune their collected grape and apple leaves dataset. The model achieved 97.87% accuracy, showing that through transfer learning CNN models' performance and efficiency can be improved. Another work in Lauguico et al. (2020) pointed out that one leaf may contain multiple leaf diseases in real life, thus, the authors used montage images to create the leaves which contain multiple diseases by combining nine pictures into one. Three pre-trained networks AlexNet, GoogLeNet & ResNet-18 are tested, which achieved 95.65%, 92.29% and 89.49% accuracy respectively. In Moyazzoma et al. (2021), a pre-trained MobileNetV2 is used to classify 21 classes of healthy and diseased leaves (7800 images, resized to 224×224 pixels). Each class has 200 training samples, 100 validation samples and 50 test samples. The transferred MobileNet can predict diseases with 90.38% accuracy. Krishnamoorthy and Parameswari (2021) transferred pre-trained VGG-16, ResNet50 and InceptionV3 to classify rice leaf diseases. The dataset contains 3 leaf diseases and 1 healthy categories (resized to 224×224 pixels). Each class of the training set has 1000 images and each class of the test set has 300 images. Finally, the fine-tuned VGG-16, ResNet50 and InceptionV3 (with different hyper-parameters) achieved 87.08%, 93.41% and 95.41% accuracy, respectively. Kibriya et al. (2021) deployed pre-trained GoogLeNet and VGG-16 for tomato leaf disease classification with accuracy of 99.23% (GoogLeNet) and 98.00% (VGG-16). A similar study can be seen in Meeradevi et al. (2020) where the authors transferred a pre-trained VGG-16 to classify tomato leaf diseases. They tested several types of VGG-16, including (i) a fresh VGG-16 (training from scratch); (ii) a classic transfer learning VGG-16 pre-trained on ImageNet; (iii) a pre-trained VGG-16 with incorporated dropout and L2 regularization; and (iv) a pre-trained VGG-16 with dropout and an attention module. In the results, they claimed that the (iv) version with dropout operation and an attention module can effectively improve the accuracy and reduce validation loss, better than other versions. The proposed model in Sharma et al. (2021) is based on pre-trained ResNet50. Only its last layer was fine-tuned and a Global average pooling layer was added with two 512-neuron dense layers on top. The result of this model, 98% F1-score, shows the advantage of transfer learning. Kaushik et al. (2020) presented a pre-trained ResNet-50 with a data augmentation method to detect and classify 6 categories of tomato leaf diseases (Plant Village). The dataset was increased by four times through data augmentation. They showed that their proposed ResNet-50 model's accuracy achieved 97% after fine-tuning the transferred model. In Hassan et al. (2021) the authors transferred common pre-trained models InceptionV3, InceptionResnetV2, MobileNetV2, and EfficientNetB0 with depthwise separable CNN method to classify diseases in entire images of Plant Village dataset. The input size was set as 224×224 pixels. And they split the dataset into three test set types which are 20%, 30% and 40%. Compare with other models, EfficientNetB0 gained the best accuracy of 99.56% on the test set. They observed that different split types have little impact on this study. Using a smaller subset (5 types of crops from Plant Village) Sai (2021) tested fine-tuning MobileNet and InceptionV3 models. In this work, the leaf images were all processed by the segmentation method, and the two models achieved 99.62% accuracy and 99.74% accuracy, respectively.

Take-home messages

1. Both data and model augmentation can help improve the performance and robustness of machine learning approaches for leaf disease classification. More attention can be seen in transfer learning where pre-trained models can be reused and augment the learning on leaf images.
 2. Although data augmentation can be useful some researchers are skeptical about its effect. This is because some data augmentation methods (e.g., random cropping, colour transformation) can change the semantics of original images, which may create misleading images and reduce the performance of classification models Wang et al. (2019).
 3. More attention is being paid to transfer learning, as can be seen in table 8 are satisfactory. This is reasonable as there are abundant pre-trained models on image data available for public use.
 4. There can be promising ideas for combining data augmentation and model augmentation. However, this study has not been addressed properly. We would encourage more studies in this direction.
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6 Applications

In this section, we will review different leaf disease classification applications, from prototyping/lab-based products to commercialised software. We categorise the applications into: Web-based apps, Mobile apps, and Devices & Hardware.

6.1 Web-based apps

Website-based applications are always the first choice of industry or researchers because it is easy to use and not limited to hardware configuration. The user could submit a picture from a computer or a mobile phone, which was captured by a camera, to get predicted results in real time.

Several examples of web-based apps are shown in Table 9. For example, Plant Disease Identifier (<https://cropify.herokuapp.com/>) is a website to provide tomato and potato leaf disease classification. A user only needs to choose a picture of the leaf to submit then will get the predicted result shortly. A rice disease classification system can be deployed on a website and WhatsApp (see Fig. 5b). This system can diagnose three diseases of rice (based on a CNN model), and identify the severity of the diseased area (percentage, based on image segmentation). The dataset used here is the HCI Rice Leaf Diseases Dataset which contains 136 images of three rice diseases. The accuracy of this system is 85.7% Wadhawan et al. (2020).

6.2 Mobile apps

In recent years, mobile apps became more popular. Mobile apps can bring better user interface and user experience with the development and popularity of smartphones.

There are some examples of mobile apps for leaf disease classification from the industry. CropsAI is an iOS mobile app which can predict the common leaf diseases of 5 species (Corn, Wheat, Tomato, Soybeans & Rice). Plants Disease Identification is a popular iOS mobile app with a price of \$2.99 on the App Store. Agrio is another mobile app which supports both Android and iOS. It claimed to have an AI-based alert system (needs remote sensors) that will notify the subscribed users and provide written preventative measures when detecting or expecting diseases or pests. Plantix is an Android mobile app which

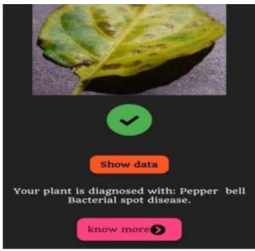
Table 9 Various applications

Name/Paper	Type	Year	Working area	Features	Other
Rice plant leaf disease classification & severity estimation Wadhawan et al. (2020)	Web & WhatsApp	2020	Rice leaf diseases	CNN + HCI Rice Leaf Diseases ¹	Accuracy 85.7% see Fig. 5b
Plant disease identifier	Website	N/A	Tomato & Potato leaf diseases	Plant Village (Tomato & Potato)	https://cropify.herokuapp.com/
Tomato leaf disease detection & classification Paymode et al. (2021)	Mobile App	2021	Tomato leaf diseases	CNN + Plant Village (Tomato)	Accuracy 97%
Agriculture Field Monitoring & Plant Leaf Disease Classification Nalawade et al. (2020)	Mobile App	2020	Plant leaf diseases	CNN + Plant Village (Part)	Accuracy 87.43% see Fig. 5a
A mobile-based system Ahmed and Reddy (2021)	Mobile APP	2021	Plant leaf diseases	Leaves Data (website) + Plant Village (Part) & CNN	Accuracy 94%, see Fig. 5g, h, https://github.com/ahmed-pvamu/Agro-Disease-Detector
Agrio	Mobile App	N/A	Plant leaf diseases	AI-based alert system, Android & iOS support	https://agrio.app/
CropsAI	Mobile App	2020	Plant leaf diseases	5 species (Corn, Wheat, Tomato, Soy beans & Rice), with remote sensing technology & iOS support	https://download.cnet.com/CropsAI/3000-20418_4-78607761.html
Plants disease identification	Mobile App	N/A	Plant leaf diseases	iOS support, Price: \$2.99	https://apps.apple.com/us/app/plants-disease-identification/id1487234676
Plantix	Mobile App	N/A	Plant leaf diseases	Cover 30 major crops, provides a community & Android support	https://plantix.net/en/
Leaf doctor	Mobile App	2014	Plant leaf diseases	Provides disease severity estimation & iOS Support	See Figs. 5i–k, https://apps.apple.com/us/app/leaf-doctor/id874509900
Robotic vehicle (Automated classification of leaf diseases) Nooraiyeen (2020)	Device	2020	Basil/Tulsi leaf diseases	K-Means & SVM + Basil/Tulsi leaves (self)	See Fig. 5c, d

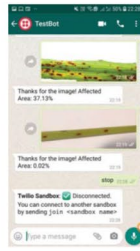
Table 9 (continued)

Name/Paper	Type	Year	Working area	Features	Other
Smart glass (real-time Leaf disease classification) Ponnusamy et al. (2020)	Device	2020	Tomato leaf diseases	YOLOv3 & CNN + Tomato Leaves (Self)	Accuracy 82.38% See Fig. 5e
A framework with Raspberry Pi Camera Chouhan et al. (2021)	Device	2021	Tree leaf diseases	Fuzzy based function network + tree leaves (self)	Avg specificity 80.66%
A IoT handheld device Gajjar et al. (2021)	Device	2021	Plant leaf diseases	Leaves dataset (self) + Plant Village (Part) & MobileNet + CNN	Accuracy 96.88%
A plant disease classification Drone Albattah et al. (2022)	Device	2022	Plant leaf diseases	Plant Village (Whole) + Pre-trained EfficientNetV2-B4, a Quadcopter DJI Phantom 3 Drone	Accuracy 99.99%
Agremo drones project	Device	N/A	Spot disease & weed infestations	Drones can automatically work on large-scale farms	https://www.agremo.com/cases/studies/using-drones-to-spot-disease-and-weed-infestations-in-sugar-beet/

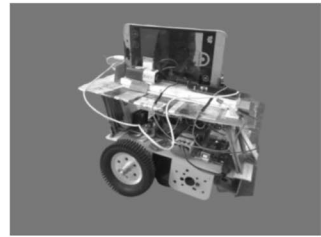
See Table 3



(a) Prediction Result (Mobile App) [74]



(b) Prediction Result (WhatsApp Interface) [8]



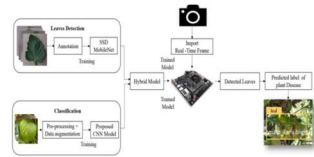
(c) The Robotic Car [75]



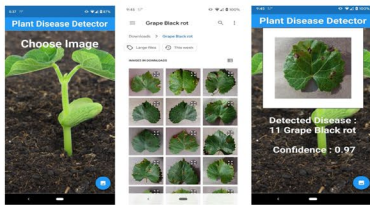
(d) Prediction Result (Robotic Car) [75]



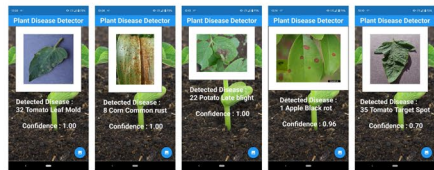
(e) Smart Glass [9]



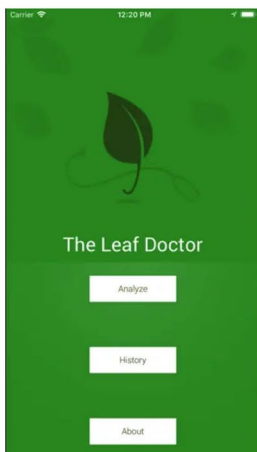
(f) The embedded platform [3]



(g) A Mobile-Based System (Interface) [54]



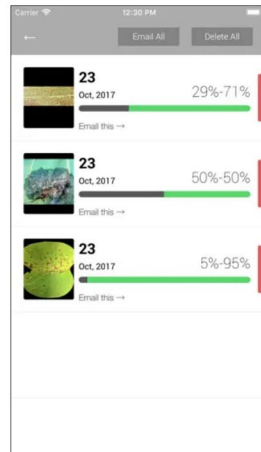
(h) A Mobile-Based System (Results) [54]



(i) Leaf Doctor Interface



(j) Leaf Doctor (Selected)



(k) Leaf Doctor (Results)

Fig. 5 Various applications of ML technologies

can classify leaf diseases of 30 main crops. It could provide instant disease classification and treatment advice. Notably, Plantix can have the largest online farmers and agricultural specialists community in the world Siddiqua et al. (2022). Users of Plantix could gain and share knowledge and help each other. Leaf Doctor was a mobile app created by the University of Hawaii, only available on the iOS system. Leaf Doctor supports leaf disease classification and provides disease severity estimation (see Fig. 5i–k). The limitation of the mobile app is the software may be limited to smartphone systems and configuration. If a smartphone has a low configuration or outdated system, it will not work properly or will run the software slowly.

From the research community, both Nalawade et al. (2020) and Paymode et al. (2021) designed a mobile app for leaf disease classification. The app in Paymode et al. (2021) can classify tomato leaf diseases. Its training dataset was from tomato leaves of Plant Village and the prediction model was based on CNN. They showed that their app could achieve 97% accuracy. Differently, the mobile app in Nalawade et al. (2020) can provide disease classification and real-time field factors monitoring (e.g., temperature, humidity, moisture) (see Fig. 5a). It was based on a CNN model which was trained on part of the Plant Village dataset. The authors demonstrated that their app can achieve 87.43% accuracy on leaf disease prediction.

6.3 Devices and hardware

Devices or custom hardware are always required by professional agricultural specialists or researchers because the specific hardware can support more computing power and more reliable performance. In Ponnusamy et al. (2020) a study pointed out that existing deep learning approaches would need high processing power and may not be suitable for low-budget mobile devices. However, the high configuration will require more capital investment and professional technical capability requirements and training. We show some examples from research as follows. In Nooraiyeen (2020) a robotic vehicle was designed and developed (see Fig. 5c) to detect Basil/Tulsi leaf diseases. Its components include a microcontroller, Bluetooth module, camera module and remote computer system. In the image detection module of the system, they used K-Means Clustering and SVM Classifier through MATLAB software. Users could get the prediction result from the software interface (see Fig. 5d). In Chouhan et al. (2021) a novel framework (named IoT_FBFN) was proposed. This framework is based on Fuzzy Based Function Network (FBFN) with IoT technology. It can capture real-time leaf images through the Raspberry Pi camera and transmit them to the system through the internet for FBFN network to classify diseases. They trained the system using a dataset of about 470 trees planted alongside the road in India. They demonstrated that the proposed system can achieve 80.66% average specificity and 80.18% average sensitivity, better than K-means and SVM. A handheld device (Embedded Platform) system was developed in Gajjar et al. (2021) (see Fig. 5f). With this handheld device, the classification accuracy rate can reach 96.88%. The device will first detect leaves using a camera then divide the image and localise the leaves through data annotation and MobileNet. This module was trained on 338 leaf images they collected, 52 images online and 111 images from Plant Village. Finally, a custom CNN was used to classify diseases. This CNN was trained on 20 categories of Plant Village (apple, corn, potato & tomato). The system has a certain robustness capability against various conditions (e.g., weather, illumination & background). An interesting device, named Smart Glass, was developed in Ponnusamy et al. (2020). This wearable device can be more convenient than

the hand-held devices mentioned previously. It was based on a Raspberry Pi Zero W and can identify whether the leaf is healthy or not in real-time (see Fig. 5e). The classification module used in Smart Glass is a transfer learning approach with YOLOv3 + CNN architecture fine-tuned on 304 tomato leaf images from farms (split into two categories: healthy and unhealthy). The proposed model can achieve an average accuracy of 82.38%.

Besides hand-held and wearable devices, Unmanned Aerial Vehicles (UAVs) are attracting more attention Ahmed and Reddy (2021); Albattah et al. (2022). UAVs have great potential in agriculture in the future. In Albattah et al. (2022), a team designed a drone (quadcopter DJI Phantom 3) with pre-trained EfficientNetV2-B4 to detect leaf diseases. The classification module was trained on Plant Village and achieved near-perfect accuracy of 99.99%. In the industry, American company Agremo started using drones to detect leaf diseases and weeds in sugar beet farms. Drones are especially suitable for continuous inspection and work on large-scale farms. They alleged their drones can provide plant counts, location data of certain weeds and diseases, or irrigation problem identification (water stress). The data of drones collected could produce data visualization easily for farmers analysing leaf diseases, weeds, water issues and so on.

Take-home messages

1. A wide range of apps and devices have been built using machine learning techniques (mostly deep learning).
 2. Mobile apps are becoming more popular than web apps for individual users thanks to their compactness and mobility. Meanwhile, UAVs (drones) have potential in large-scale farming. Some prototypes of hand-held and wearable devices were tested but they are not ready for commercialisation.
-

7 Conclusions

Despite machine learning techniques have been widely used in leaf disease classification, to our best knowledge, a comprehensive and up-to-date survey which can cover related available data, techniques and applications is still desired by the industry and research community. Therefore, in this paper, we surveyed about 100 recent related articles, collected and listed a series of public datasets which can be researched, analysed state-of-the-art machine learning approaches (i.e., shallow learning, deep learning & augmented learning) and reviewed feasible applications in academia and industry. We have the following findings. In the data part, Maize Leaf (NLB) dataset could be the largest public dataset of single plant species at present while Plant Village is the most popular dataset. Plant Village, Plant Leaves and Plantae_K are all laboratory datasets which can be useful for prototyping and evaluating machine learning models. However, real-field datasets, including PlantDoc would provide a more comprehensive evaluation and support for realistic applications. For technologies, shallow machine learning requires feature extraction from images Applalaaidu and Kumaravelan (2021) to be useful for the disease classification task. The two most common methods are K-means clustering and grey-level co-occurrence matrix (GLCM), in which GLCM is more recommended. A combination of features is also encouraged, as it can help improve performance. Support vector machine (SVM) was the most common method for leaf disease classification in shallow machine learning. It is very suitable for both smaller (more likely to be linear) or non-linear datasets Thet et al. (2020). Its better performance in comparison to other classifiers is evident in several studies. However,

if suitable features are selected, KNN or RF also can achieve better accuracy. Relative to shallow learning, Deep learning models have been proven useful and more effective than shallow learning for leaf disease classification which should be recommended in real-life applications due to their high accuracy. It is also more convenient as we can get rid of the feature extraction steps and minimise the manual effort for data processing. The common off-the-shelf deep learning models are CNN, AlexNet, VGG-16, ResNet, EfficientNet, Inception and MobileNet. Custom CNNs are highly encouraged as we should design an optimal model for different tasks. It was evident that custom CNNs perform better than off-the-shelf models. We can see that the datasets used in deep learning papers were relatively larger than in other studies. This is consistent with the fact that deep learning models are usually data-hungry. Most of the studies focus on the performance (accuracy) aspect of the task while a more comprehensive comparison with compactness and efficiency is still missing. There are a few papers that addressed these issues, for example, Sharma et al. (2020) evaluates models' speed and Agarwal et al. (2020) evaluates models' storage space. Recent research proved that both data and model augmentation methods can help improve the performance and robustness of deep learning for leaf disease classification. More attention is on transfer learning where pre-trained models can be reused and augment the learning on leaf images. Although data augmentation can be useful some researchers are sceptical about its effect. The reason may be some data augmentation methods (e.g., random cropping, colour transformation) can change the semantics of original images, which may create misleading images and reduce the performance of classification models Wang et al. (2019). The popularity of transfer learning is reasonable as there are abundant pre-trained models on image data (e.g., ImageNet) available for public use now. For applications, section 6 showed that a wide range of applications (software) and devices (hardware) have been built using machine learning techniques (mostly deep learning). Mobile applications are becoming more popular than web apps for individual users thanks to their compactness and mobility. Meanwhile, UAVs (drones) have advantages and potential in large-scale farming. Some prototypes of hand-held and wearable devices were tested but they may not be ready for commercialisation. Last but certainly not least is the explainability of Machine Learning methods. With the increasing adoption of Machine Learning in the agriculture industry, there arises a pressing demand for models to be transparent and explainable. This may be important for enabling farmers to understand the decision-making process and trust this new technology method.

Based on the above findings, we have the following suggestions.

1. The available datasets listed are useful for domain-adaptation and multi-task learning, however, this is largely missing in the current literature.
2. A machine learning model should learn from different datasets in a compositional manner where the model can effectively adapt to new tasks/datasets added in.
3. For small datasets with a small set of disease classes, simple methods may achieve good results.
4. Many studies use different experiment settings, including different partitions for training/validation/test which makes their results difficult to compare. Therefore, a benchmarking study is needed and encouraged.
5. The research on explainability in this area remains worth attention, as the industry still requires a means to effectively explain decision-making by Machine Learning models to enable user understanding.

6. There can be a promising idea of combining data augmentation and model augmentation. However, this study has not been addressed properly.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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References

- Agarwal M, Gupta SK, Biswas KK (2019) Grape disease identification using convolution neural network. In: 2019 23rd International Computer Science and Engineering Conference (ICSEC), pp. 224–229. <https://doi.org/10.1109/ICSEC47112.2019.8974752>
- Agarwal M, Singh A, Arjaria S, Sinha A, Gupta S (2020) Toled: tomato leaf disease detection using convolution neural network. *Procedia Comput Sci* 167:293–301
- Agarwal D, Chawla M, Tiwari N (2021) Plant leaf disease classification using deep learning: A survey. In: 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), pp. 643–650. <https://doi.org/10.1109/ICIRCA51532.2021.9544640>
- Ahil MN, Vanitha V, Rajathi N (2021) Apple and grape leaf disease classification using mlp and cnn. In: 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), pp. 1–4. <https://doi.org/10.1109/ICAECA52838.2021.9675567>
- Ahmed AA, Reddy GH (2021) A mobile-based system for detecting plant leaf diseases using deep learning. *AgriEngineering* 3(3):478–493. <https://doi.org/10.3390/agriengineering3030032>
- Albattah W, Javed A, Nawaz M, Masood M, Albahli S (2022) Artificial intelligence-based drone system for multiclass plant disease detection using an improved efficient convolutional neural network. *Front Plant Sci* 13:808380
- Anandhakrishnan T, Jaisakthi S (2020) Identification of tomato leaf disease detection using pretrained deep convolutional neural network models. *Scalable Comput: Pract Exp* 21(4):625–635
- Applalanaidu MV, Kumaravelan G (2021) A review of machine learning approaches in plant leaf disease detection and classification. In: 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), pp. 716–724. <https://doi.org/10.1109/ICICV50876.2021.9388488>
- Arun Pandian J, Geetharamani G, Annette B (2019) Data augmentation on plant leaf disease image dataset using image manipulation and deep learning techniques. In: 2019 IEEE 9th International Conference on Advanced Computing (IACC), pp. 199–204. <https://doi.org/10.1109/IACC48062.2019.8971580>
- Ashok S, Kishore G, Rajesh V, Suchitra S, Sophia SGG, Pavithra B (2020) Tomato leaf disease detection using deep learning techniques. In: 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 979–983. <https://doi.org/10.1109/ICCES48766.2020.9137986>
- Atila U, Ucar M, Akyol K, Ucar E (2021) Plant leaf disease classification using efficientnet deep learning model. *Ecol Inform* 61:101182. <https://doi.org/10.1016/j.ecoinf.2020.101182>
- Bangari S, Rachana P, Gupta N, Sudi PS, Baniya KK (2022) A survey on disease detection of a potato leaf using cnn. In: 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), pp. 144–149. <https://doi.org/10.1109/ICAIS53314.2022.9742963>
- Barburiceanu S, Terebes R, Meza S (2020) Grape leaf disease classification using lbp-derived texture operators and colour. In: 2020 IEEE International Conference on Automation, Quality and Testing, Robotics (AQTR), pp. 1–6. <https://doi.org/10.1109/AQTR49680.2020.9130019>

- Bari BS, Islam MN, Rashid M, Hasan MJ, Razman MA, Musa RM, Ab Nasir AF, Majeed AP (2021) A real-time approach of diagnosing rice leaf disease using deep learning-based faster r-cnn framework. *PeerJ Comput Sci* 7:432
- Bhagat M, Kumar D (2022) A comprehensive survey on leaf disease identification and classification. *Multimed Tools Appl* 81(23):33897–33925. <https://doi.org/10.1007/s11042-022-12984-z>
- Bharate AA, Shirdhonkar MS (2020) Classification of grape leaves using knn and svm classifiers. In: 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), pp. 745–749. <https://doi.org/10.1109/ICCMC48092.2020.ICCMC-000139>
- Bhowmik S, Talukdar AK, Kumar Sarma K (2020) Detection of disease in tea leaves using convolution neural network. In: 2020 Advanced Communication Technologies and Signal Processing (ACTS), pp. 1–6. <https://doi.org/10.1109/ACTS49415.2020.9350413>
- Bhujel A, Kim N-E, Arulmozhi E, Basak JK, Kim H-T (2022) A lightweight attention-based convolutional neural networks for tomato leaf disease classification. *Agriculture* 12(2):228. <https://doi.org/10.3390/agriculture12020228>
- Bir P, Kumar R, Singh G (2020) Transfer learning based tomato leaf disease detection for mobile applications. In: 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON), pp. 34–39. <https://doi.org/10.1109/GUCON48875.2020.9231174>
- Chaudhari V, Patil M (2020) Banana leaf disease detection using k-means clustering and feature extraction techniques. In: 2020 International Conference on Advances in Computing, Communication Materials (ICACCM), pp. 126–130. <https://doi.org/10.1109/ICACCM50413.2020.9212816>
- Chouhan SS, Singh UP, Jain S (2020) Applications of computer vision in plant pathology: a survey. *Arch Comput Methods Eng: State Art Rev* 27(2):611
- Chouhan SS, Singh UP, Jain S (2021) Automated plant leaf disease detection and classification using fuzzy based function network. *Wirel Pers Commun* 121:1757–1779
- Chowdhury MEH, Rahman T, Khandakar A, Ayari MA, Khan AU, Khan MS, Al-Emadi N, Reaz MBI, Islam MT, Ali SHM (2021) Automatic and reliable leaf disease detection using deep learning techniques. *AgriEngineering* 3(2):294–312
- Dang-Ngoc H, Cao TNM, Dang-Nguyen C (2021) Citrus leaf disease detection and classification using hierarchical support vector machine. In: 2021 International Symposium on Electrical and Electronics Engineering (ISEE), pp. 69–74. <https://doi.org/10.1109/ISEE51682.2021.9418680>
- Das D, Singh M, Mohanty SS, Chakravarty S (2020) Leaf disease detection using support vector machine. In: 2020 International Conference on Communication and Signal Processing (ICCS), pp. 1036–1040. <https://doi.org/10.1109/ICCS48568.2020.9182128>
- Divya P, Palanive D, Rajan Nithya K (2021) Review on various deep learning methods adopted to improve the plant leaf disease classification in precision agriculture. *Grenze Int J Eng Technol* 7(1):49–54
- Ekanayake E, Nawarathna R (2021) Novel deep learning approaches for crop leaf disease classification: A review. In: 2021 International Research Conference on Smart Computing and Systems Engineering (SCSE), vol. 4, pp. 49–52. <https://doi.org/10.1109/SCSE53661.2021.9568324>
- Gadade HD, Kirange DK (2020) Tomato leaf disease diagnosis and severity measurement. In: 2020 Fourth World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), pp. 318–323. <https://doi.org/10.1109/WorldS450073.2020.9210294>
- Gajjar R, Gajjar N, Thakor VJ, Patel NP, Ruparelia S (2021) Real-time detection and identification of plant leaf diseases using convolutional neural networks on an embedded platform. *The Visual Computer: International Journal of Computer Graphics*, 1
- Geetharamani G, Pandian A (2019) Identification of plant leaf diseases using a nine-layer deep convolutional neural network. *Comput Electr Eng* 76:323–338
- Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, Courville A, Bengio Y (2014) Generative adversarial nets. In: Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N., Weinberger, K.Q. (eds.) *Advances in Neural Information Processing Systems*, vol. 27. Curran Associates, Inc. <https://proceedings.neurips.cc/paper/2014/file/5ca3e9b122f61f8f0649c97b1afccf3-Paper.pdf>
- Goodfellow I, Bengio Y, Courville A (2016) *Deep Learning*. MIT Press. <http://www.deeplearningbook.org>
- Guan X (2021) A novel method of plant leaf disease detection based on deep learning and convolutional neural network. In: 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP), pp. 816–819. <https://doi.org/10.1109/ICSP51882.2021.9408806>
- Hassan SM, Maji AK, Jasiński M, Leonowicz Z, Jasińska E (2021) Identification of plant-leaf diseases using cnn and transfer-learning approach. *Electronics* 10(12):1388. <https://doi.org/10.3390/electronics10121388>
- Hu G, Wang H, Zhang Y, Wan M (2021) Detection and severity analysis of tea leaf blight based on deep learning. *Comput Electr Eng* 90:107023

- Huang Z, Qin A, Lu J, Menon A, Gao J (2020) Grape leaf disease detection and classification using machine learning. In: 2020 International Conferences on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics), pp. 870–877. <https://doi.org/10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics50389.2020.00150>
- Hughes DP, Salath'e M (2015) An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing. *CoRR abs/1511.08060*. [arXiv:1511.08060](https://arxiv.org/abs/1511.08060)
- Hughes DP, Salathe M (2016) An open access repository of images on plant health to enable the development of mobile disease diagnostics
- Jana S, Begum AR, Selvaganesan S, Suresh P (2021) Deep belief network based disease detection in pepper leaf for farming sector. *Turk J Physiother Rehabil* 32(2):994–1002
- Jayaprakash K, Balamurugan SP (2021) An efficient hand-crafted features with machine learning-based plant leaf disease diagnosis and classification model. *Turk J Physiother Rehabil* 32(2):1683–1698
- Jepkoech J, Mugo DM, Kenduiyo BK, Too EC (2021) Arabica coffee leaf images dataset for coffee leaf disease detection and classification. *Data Br* 36:107142. <https://doi.org/10.1016/j.dib.2021.107142>
- Kathiresan G, Anirudh M, Nagharjun M, Karthik R (2021) Disease detection in rice leaves using transfer learning techniques. *J Phys: Conf Ser* 1911(1):012004. <https://doi.org/10.1088/1742-6596/1911/1/012004>
- Kaushik M, Prakash P, Ajay R, Veni S (2020) Tomato leaf disease detection using convolutional neural network with data augmentation. In: 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 1125–1132. <https://doi.org/10.1109/ICCES48766.2020.9138030>
- Kawatra M, Agarwal S, Kapur R (2020) Leaf disease detection using neural network hybrid models. In: 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA), pp. 225–230. <https://doi.org/10.1109/ICCCA49541.2020.9250885>
- Kibriya H, Rafique R, Ahmad W, Adnan SM (2021) Tomato leaf disease detection using convolution neural network. In: 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST), pp. 346–351. <https://doi.org/10.1109/IBCAST51254.2021.9393311>
- Kirti Rajpal N (2020) Black rot disease detection in grape plant (*vitis vinifera*) using colour based segmentation amp; machine learning. In: 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), pp. 976–979. <https://doi.org/10.1109/ICACCCN51052.2020.9362812>
- Krishnamoorthy N, Parameswari VRL (2021) Rice leaf disease detection via deep neural networks with transfer learning for early identification. *Turk J Physiother Rehabil* 32(2):1087–1097
- Kumar L, Singh DK (2021) Analyzing computational response and performance of deep convolution neural network for plant disease classification using plant leave dataset. In: 2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT), pp. 549–553. <https://doi.org/10.1109/CSNT51715.2021.9509632>
- Kumar V, Arora H, Harsh Sisodia J (2020a) Resnet-based approach for detection and classification of plant leaf diseases. In: 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 495–502. <https://doi.org/10.1109/ICESC48915.2020.9155585>
- Kumar S, Prasad K, Srilekha A, Suman T, Rao BP, Vamshi Krishna JN (2020b) Leaf disease detection and classification based on machine learning. In: 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), pp. 361–365. <https://doi.org/10.1109/ICSTCEE49637.2020.9277379>
- Kumar R, Chug A, Singh AP, Singh D (2022) A systematic analysis of machine learning and deep learning based approaches for plant leaf disease classification: a review. *J Sens* 2022:1–13. <https://doi.org/10.1155/2022/3287561>
- Lakshmi RK, Nickolas S (2020) Deep learning based betelvine leaf disease detection (piper betel.). In: 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA), pp. 215–219. <https://doi.org/10.1109/ICCCA49541.2020.9250911>
- Lamba S, Baliyan A, Kukreja V (2022) Gan based image augmentation for increased cnn performance in paddy leaf disease classification. In: 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp. 2054–2059. <https://doi.org/10.1109/ICACITE53722.2022.9823799>
- Lauguico S, Concepcion R, Ruzcko Tobias R, Bandala A, Rhay Vicerra R, Dadios E (2020) Grape leaf multi-disease detection with confidence value using transfer learning integrated to regions with

- convolutional neural networks. In: 2020 IEEE REGION 10 CONFERENCE (TENCON), pp. 767–772. <https://doi.org/10.1109/TENCON50793.2020.9293866>
- Lecun Y, Bottou L, Bengio Y, Haffner P (1998) Gradient-based learning applied to document recognition. *Proc IEEE* 86(11):2278–2324. <https://doi.org/10.1109/5.726791>
- Li L, Zhang S, Wang B (2021) Plant disease detection and classification by deep learning—a review. *IEEE Access* 9:56683–56698. <https://doi.org/10.1109/ACCESS.2021.3069646>
- Lu Y, Young S (2020) A survey of public datasets for computer vision tasks in precision agriculture. *Comput Electron Agric* 178:105760. <https://doi.org/10.1016/j.compag.2020.105760>
- Meeradevi VR, Mundada MR, Sawkar SP, Bellad RS., eerthi PS (2020) Design and development of efficient techniques for leaf disease detection using deep convolutional neural networks. In: 2020 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), pp. 153–158 (2020). <https://doi.org/10.1109/DISCOVER50404.2020.9278067>
- Metre VA, Sawarkar SD (2021) Research opportunities for the detection and classification of plant leaf diseases. In: 2021 2nd Global Conference for Advancement in Technology (GCAT), pp. 1–8. <https://doi.org/10.1109/GCAT52182.2021.9587775>
- Metre VA, Sawarkar SD (2022) Reviewing important aspects of plant leaf disease detection and classification. In: 2022 International Conference for Advancement in Technology (ICONAT), pp. 1–8. <https://doi.org/10.1109/ICONAT53423.2022.9725870>
- Mohona SA, Aktar S, Ahamad MM (2021) Efficient computation of leaf disease classification techniques using deep learning. In: 2021 3rd International Conference on Electrical and Electronic Engineering (ICEEE), pp. 149–152. <https://doi.org/10.1109/ICEEE54059.2021.9718941>
- Moyazzoma R, Hossain MAA, Anuz MH, Sattar A (2021) Transfer learning approach for plant leaf disease detection using cnn with pre-trained feature extraction method mobilnetv2. In: 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), pp. 526–529. <https://doi.org/10.1109/ICREST51555.2021.9331214>
- Mukhopadhyay S, Paul M, Pal R, De D (2021) Tea leaf disease detection using multi-objective image segmentation. *Multimed Tools Appl: Int J* 80(1):753
- Mureşan HB, Coroiu AM, Călin AD (2020) Detecting leaf plant diseases using deep learning: A review. In: 2020 International Conference on Software, Telecommunications and Computer Networks (SoftCOM), pp. 1–6. <https://doi.org/10.23919/SoftCOM50211.2020.9238318>
- Mwebeze E, Gebru T, Frome A, Nsumba S, Tusubira J (2019) iCassava 2019 Fine-Grained Visual Categorization Challenge
- Nagaraju Y, Venkatesh Swetha S, Stalin S (2020) Apple and grape leaf diseases classification using transfer learning via fine-tuned classifier. In: 2020 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT), pp. 1–6. <https://doi.org/10.1109/ICMLANT50963.2020.9355991>
- Nagaraju M, Chawla P, Upadhyay S, Tiwari R (2022) Convolution network model based leaf disease detection using augmentation techniques. *Expert Syst* 39(4):12885. <https://doi.org/10.1111/exsy.12885>
- Naik BN, Malmathanraj R, Palanisamy P (2022) Detection and classification of chilli leaf disease using a squeeze-and-excitation-based cnn model. *Ecol Inform* 69:101663. <https://doi.org/10.1016/j.ecoinf.2022.101663>
- Nalawade R, Nagap A, Jindam L, Ugale M (2020) Agriculture field monitoring and plant leaf disease detection. In: 2020 3rd International Conference on Communication System, Computing and IT Applications (CSCITA), pp. 226–231. <https://doi.org/10.1109/CSCITA47329.2020.9137805>
- Nisar N, Awasthi A, Chhabra M, Abidi AI (2020) Image based recognition of plant leaf diseases: A review. In: 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), pp. 373–378. <https://doi.org/10.1109/I-SMAC49090.2020.9243434>
- Nooraiyeen A (2020) Robotic vehicle for automated detection of leaf diseases. In: 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), pp. 1–6. <https://doi.org/10.1109/CONECCT50063.2020.9198326>
- Padol PB, Yadav AA (2016) Svm classifier based grape leaf disease detection. In: 2016 Conference on Advances in Signal Processing (CASP), pp. 175–179. <https://doi.org/10.1109/CASP.2016.7746160>
- Panwar A, Gupta S, Chaube N, Gupta S, Kapruwan A (2022) Classification of apple leaf diseases using distinct machine learning algorithms. In: 2022 IEEE Delhi Section Conference (DELCON), pp. 1–6. <https://doi.org/10.1109/DELCON54057.2022.9753629>
- Paymode AS, Magar SP, Malode VB (2021) Tomato leaf disease detection and classification using convolution neural network. In: 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), pp. 564–570. <https://doi.org/10.1109/ESCI50559.2021.9397001>
- Ponnusamy V, Coumaran A, Shunmugam AS, Rajaram K, Senthilvelavan S (2020) Smart glass: Real-time leaf disease detection using yolo transfer learning. In: 2020 International Conference on

- Communication and Signal Processing (ICCSP), pp. 1150–1154. <https://doi.org/10.1109/ICCSP48568.2020.9182146>
- Prajapati H, Shah J, Dabhi V (2017) Detection and classification of rice plant diseases. *Intell Decis Technol* 11:357–373. <https://doi.org/10.3233/IDT-170301>
- Raina S, Gupta A (2021) A study on various techniques for plant leaf disease detection using leaf image. In: 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), pp. 900–905. <https://doi.org/10.1109/ICAIS50930.2021.9396023>
- Raja PV, Sangeetha K, B A N, M S, S S S (2022) Convolutional neural networks based classification and detection of plant disease. In: 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), pp. 1484–1488. <https://doi.org/10.1109/ICCMC53470.2022.9753846>
- Rajesh B, Sai Vardhan MV, Sujihelen L (2020) Leaf disease detection and classification by decision tree. In: 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), pp. 705–708. <https://doi.org/10.1109/ICOEI48184.2020.9142988>
- Ramya R, Sona R, Mohanapriya S, Sri nivas C, Keerthana ST (2021) Tomato leaf disease detection and classification with severity estimation using convolutional neural networks. *Grnze Int J Eng Technol* 7(1):960–966
- Rauf HT, Saleem BA, Lali MIU, Khan MA, Sharif M, Bukhari SAC (2019) A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning. *Data Br* 26:104340. <https://doi.org/10.1016/j.dib.2019.104340>
- Sai DC (2021) A review on crop disease detection using deep learning. *J Netw Inf Secur* 9(1):18–22
- Sai Reddy SB (2022) Neeraja: plant leaf disease classification and damage detection system using deep learning models. *Multimed Tools Appl* 81(17):24021–24040. <https://doi.org/10.1007/s11042-022-12147-0>
- Saraswathi RV, Bitla V, Radhika P, Kumar TN (2021) Leaf disease detection and remedy suggestion using convolutional neural networks. In: 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), pp. 788–794. <https://doi.org/10.1109/ICCMC51019.2021.9418013>
- Sardogan M, Tuncer A, Ozen Y (2018) Plant leaf disease detection and classification based on cnn with lvq algorithm. In: 2018 3rd International Conference on Computer Science and Engineering (UBMK), pp. 382–385. <https://doi.org/10.1109/UBMK.2018.8566635>
- Shahidur Harun Rummy SM, Arefin Hossain MI, Jahan F, Tanvin T (2021) An iot based system with edge intelligence for rice leaf disease detection using machine learning. In: 2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), pp. 1–6. <https://doi.org/10.1109/IEMTRONICS52119.2021.9422499>
- Shaji AP, Hemalatha S (2022) Data augmentation for improving rice leaf disease classification on residual network architecture. In: 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), pp. 1–7. <https://doi.org/10.1109/ACCAI53970.2022.9752495>
- Sharma P, Hans P, Gupta SC (2020) Classification of plant leaf diseases using machine learning and image preprocessing techniques. In: 2020 10th International Conference on Cloud Computing, Data Science Engineering (Confluence), pp. 480–484. <https://doi.org/10.1109/Confluence47617.2020.9057889>
- Sharma A, Rajesh B, Javed M (2021) Detection of Plant Leaf Disease Directly in the JPEG Compressed Domain using Transfer Learning Technique
- Shorten C, Khoshgoftaar TM (2019) A survey on image data augmentation for deep learning. *J Big Data* 6(1):1–48
- Siddiqua A, Kabir MA, Ferdous T, Ali IB, Weston LA (2022) Evaluating plant disease detection mobile applications: Quality and limitations. *Agronomy* 12(8):1869. <https://doi.org/10.3390/agronomy12081869>
- Singh D, Jain N, Jain P, Kayal P, Kumawat S, Batra N (2020a) Plantdoc: A dataset for visual plant disease detection. *Proceedings of the 7th ACM IKDD CoDS and 25th COMAD*. <https://doi.org/10.1145/3371158.3371196>
- Singh U, Srivastava A, Chauhan D, Singh A (2020b) Computer vision technique for detection of grape esca (black measles) disease from grape leaf samples. In: 2020 International Conference on Contemporary Computing and Applications (IC3A), pp. 110–115. <https://doi.org/10.1109/IC3A48958.2020.233281>
- Sujatha R, Chatterjee JM, Jhanjhi N, Brohi SN (2021) Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocess Microsyst* 80:103615. <https://doi.org/10.1016/j.micpro.2020.103615>
- Sunil CK, Jaidhar CD, Patil N (2020) Empirical study on multi convolutional layer-based convolutional neural network classifier for plant leaf disease detection. In: 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS), pp. 460–465. <https://doi.org/10.1109/ICIIS51140.2020.9342729>

- Surya R, Gautama E (2020) Cassava leaf disease detection using convolutional neural networks. In: 2020 6th International Conference on Science in Information Technology (ICSITech), pp. 97–102 . <https://doi.org/10.1109/ICSITech49800.2020.9392051>
- Thet KZ, Htwe KK, Thein MM (2020) Grape leaf diseases classification using convolutional neural network. In: 2020 International Conference on Advanced Information Technologies (ICAIT), pp. 147–152 (2020). <https://doi.org/10.1109/ICAIT51105.2020.9261801>
- Tulshan AS, Raul N (2019) Plant leaf disease detection using machine learning. In: 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), pp. 1–6. <https://doi.org/10.1109/ICCCNT45670.2019.8944556>
- Vijaykanth Reddy T, Sashi Rekha K (2021) Deep leaf disease prediction framework (dldpf) with transfer learning for automatic leaf disease detection. In: 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), pp. 1408–1415. <https://doi.org/10.1109/ICCMC51019.2021.9418245>
- Wadhawan R, Garg M, Sahani AK (2020) Rice plant leaf disease detection and severity estimation. In: 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS), pp. 455–459. <https://doi.org/10.1109/ICIIS51140.2020.9342653>
- Wang Q, Jia N, Breckon TP (2019) A baseline for multi-label image classification using an ensemble of deep convolutional neural networks. In: 2019 IEEE International Conference on Image Processing (ICIP), pp. 644–648. <https://doi.org/10.1109/ICIP.2019.8803793>
- Wiesner-Hanks T, Stewart EL, Kaczmar N, DeChant C, Wu H, Nelson RJ, Lipson H, Gore MA (2018) Image set for deep learning: field images of maize annotated with disease symptoms. *BMC Res Notes* 11(1):440
- Xie X, Ma Y, Liu B, He J, Li S, Wang H (2020) A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks. *Front Plant Sci* 11:751. <https://doi.org/10.3389/fpls.2020.00751>
- Zhang X, Qiao Y, Meng F, Fan C, Zhang M (2018) Identification of maize leaf diseases using improved deep convolutional neural networks. *IEEE Access* 6:30370–30377. <https://doi.org/10.1109/ACCESS.2018.2844405>

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