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SURVEY

A Review of Leaf Diseases Detection and Classification by Deep Learning

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ABSTRACT Leaf's primary function is to produce nutrients through photosynthesis and support the plant's growth. Leaf diseases caused by bacteria or other pathogens can negatively impact agricultural yields. Immediate and early diagnosis of diseases is vital for plant health. The significant development of deep learning algorithms for leaf disease classification and detection contributed to a solid tool with a robust and reliable accuracy rate. This study presents a comprehensive review of leaf disease research in the literature. It also highlights the gaps that need to be filled as well as the obstacles and problems facing research projects. The total number of papers retrieved from five electronic databases is 256. We analyzed and classified them into seven research questions. The results demonstrate that 63% of the papers are journal articles, 35% are conference papers, and 2% are workshop papers.

INDEX TERMS Classification, deep learning, leaf diseases.

I. INTRODUCTION

Agricultural products serve as the main source of economic output and revenue for most nations. There are several diseases that affect crops and have a significant impact on the productivity and income of farmers. Leaf diseases are the primary issue that reduces agricultural productivity [1]. According to the studies, 50% of crop losses are caused by plant diseases and pets [2]. Managing and controlling diseases is essential to increasing crop productivity. Keeping track of crops and diagnosing them at the right time is essential to eliminating plant diseases. Discovering diseases in the early stages enables farmers to avoid damage, lower production costs, and improve profits. Traditional diagnosis by the human eye fails to detect diseases in the plant at an early stage or misdiagnoses them [3]. Machine learning and deep learning have been widely used in agriculture and agricultural disease diagnosis and detection in recent years.

Leaf disease detection and classification at early stages are essential in agriculture. However, there are different ways to identify plant diseases. Various types of diseases have no visible symptoms, which require sophisticated analysis. Meanwhile, most diseases produce a visible spectrum on the leaf that a specialist can examine. Achieving accuracy on plant diseases requires proper monitoring skills to distinguish feature symptoms [4]. Crops are affected by many diseases and we can effectively manage their spread. In addition to minimizing crop losses, it also ensures excellent yields for economic growth [3]. We review the many types of research that have been done on plant diseases and plant disease recognition. The aim is to facilitate the research in this field that researchers have done previously in detecting and classifying leaf diseases on images using machine learning and deep learning architectures [5]. Various machine learning and deep learning methods have been used to increase classification and detection accuracy, including the k-means method, Fuzzy Logic (FL), Random Forest (RF), Artificial Neural Network (ANN), Support Vector Machine (SVM), Convolutional Neural Networks (CNNs) [6].

Image processing and cutting-edge deep learning methods are widely used to diagnose leaf diseases. Different types of popular CNN architectures have accomplished excellent jobs in training and testing the image, such as AlexNet [7], LeNet [8], InceptionV3 [9], VGGNet [2], ResNet [10], GoogLeNet [11] and DenseNet [12] significantly improves the accuracy in the detection and classification of leaf diseases [13].

Deep learning models have been used in studies on plant disease identification and classification [14]. However, these

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studies fall short of providing the comprehensive perspective needed for plant disease detection and identification. More importantly, these studies neglect important aspects such as sensors and technologies commonly used to detect diseases, disease causative agents, machine learning methods to recognize plant diseases, already detected diseases, and research techniques used to study disease detection in fields [15]. In this study, our main objectives are: Firstly, to provide a comprehensive overview of the existing literature. Secondly, to identify research gaps, patterns, and issues related to the detection and classification of leaf diseases through machine learning and deep learning.

Thus, this literature review aims to classify leaf disease through state-of-the-art detection and classification using deep learning and machine learning. The observation examines considerable research contributions and challenges, and substantial work has been done to create applications that improve deep learning architectures [16].

This paper is organized as follows: Section II outlines the background, and Section III provides a detailed overview of the study. We present and discuss our results in Section IV. The final section summarizes the conclusions presented in the paper.

II. BACKGROUND

The detection and classification of diseases on the leaf are among the hottest topics in computer vision related to agriculture and agricultural activities. Farmers use traditional methods to identify plant diseases. Manual vision leads to incorrect diagnosis and failed symptom evaluation. After AlexNet's debut, other cutting-edge DL models and architectures for image detection, segmentation, and classification emerged. The study done to identify and categorize plant diseases using well-known DL architectures is presented in this part. Additionally, in other related research papers, improved/modified DL architectures and novel visualization techniques were used to produce a better accuracy rate [17]. DL architectures produce more accurate findings than customized ML-based techniques, enabling better choices to be made. Due to the rapid advancement of hardware, DL frameworks are being extensively researched to find solutions to difficult issues in a respectably short amount of time. In the sphere of crops, DL-based approaches demonstrate cutting-edge precision and generalize well to various jobs. Different kinds of deep neural networks (DNNs) have surpassed hyperspectral evaluation in terms of efficiency [18].

A. DEEP LEARNING

Deep learning (DL) is a subset of machine learning (ML). Deep learning offers state-of-the-art products in several computer vision domains. Before deep learning, many approaches were suggested to identify plant diseases using image processing and machine learning. These methods are based on hand-crafted features that lack automation, such as SIFT, HOG, and SURF [19]. In addition, image labeling must be manually performed, making data preprocessing very expensive and time-consuming. Prior studies required a small dataset for training and testing due to these obstacles, leading to overfitting. Deep learning has many advantages in plant disease detection and classification, including an end-to-end system and the capability to exploit images directly. Deep learning can train as many images as possible, compared with traditional machine learning classifiers. The most significant advantage is that deep learning architecture achieves better accuracy results [20].

B. CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional Neural Networks (CNNs) are a state-of-the-art deep learning architecture. CNN was developed several years ago and has been applied in different domains. CNN shows excellent success, especially in computer vision-related tasks. CNN consists of two primary parts: feature extraction (learning) and classification. Feature extraction consists of various layers, convolutional ReLU, and pooling layers. Image classification comprises a fully connected layer and normalization [21].

CNN is a powerful deep-learning model for image detection and classification in various computer vision branches. CNN performs far better than traditional classifiers because it is less complicated and follows a diverse regularization approach. It can learn fundamental filters automatically and sort them accordingly [19]. CNN can train on a vast amount of data to achieve reliable results. However, this feature does not apply to traditional approaches. An additional concept that CNN models can discover with small or large datasets is transfer learning. Machine learning and deep learning have been incorporated into CNN developed in recent years. These architectures have significantly improved optimization, regularization, and structural reformulation. As a result of its revised architectural design and structure, CNN has improved significantly. The newly developed architecture features a modification to its design. CNN architectures are classified into seven classes: spatial exploitation, depth, multi-path, width, feature-map exploitation, channel boosting, and attention-oriented CNNs. LeNet, AlexNet, VGGNet, and GoogLeNet are CNN models that rely on spatial exploitation. A large number of parameters and hyperparameters characterize these models. ResNet and Inception V3 are depth-based CNN models characterized by increased depth, which is essential in supervision training. DenseNet is a multi-path-based CNN model introduced to solve vanishing gradient problems.

Inception families are width-based CNN models that improve intermediate layer output. SqueezeNet, one of the feature-map exploitation-based CNN methods, introduces an innovative block. The block comprises squeeze and excitation procedures to initiate feature-map-wise statistics. The channel-boosted CNN algorithm boosts the number of input channels. Image processing relies on image representation for model performance. Therefore, deep learning classifiers are concerned with image representation to improve the network's capacity. Residual attention neural networks (RAN) and convolutional block attention modules are attention-based CNN classifiers focusing on image localization and recognition. The purpose of attention in CNN is to enable the network to learn objects [22].

C. TYPES OF LEAF DISEASES

There are two main types of leaf diseases: biotic and abiotic agents. Living organisms are called biotics, and nonliving organisms are called abiotics. Diseases caused by biotic agents include insects, bacteria, fungi, and viruses. At the same time, an abiotic agent includes extremes of temperature, excess moisture, poor light, poor soil, and insufficient nutrients. Although leaf diseases cause significant crop losses and directly affect the economy and animal and human health, yield losses can be reduced and specific toxoids can be adopted to battle specific pathogens if diseases are appropriately diagnosed and detected early [23].

III. LITERATURE REVIEW PLANNING

We revise our literature review plan in this section. According to Bischoff et al. [15], this methodology aims to facilitate more reliable and trustworthy discovery by reducing bias through a precise review approach. This planning section presents the requirements and the stimulation for conducting a literature review. In addition, successful outcome protocols for literature reviews are substantial components [16]. Table 1 presents the description of the research questions.

A. GOAL AND RESEARCH QUESTION

This review aims to contribute to a broad review of the latest literature and to reveal research gaps, challenges, and barriers that are valuable to explore from the perspective of leaf diagnosis, detection, and classification. The main research question of the literature review that we plan to answer is: Which machine and deep learning algorithms have been used to detect and classify leaf diseases, and which method gives better accuracy results?

B. RESEARCH STRATEGY

This literature review examines studies with relevant results and applies them to leaf diseases. Articles are selected according to their topic, related to leaf diseases and using machine learning and deep learning algorithms. Figure 1 shows the various sources used as our search databases. Those databases provide authenticated articles, conferences, literature reviews, and workshops. Various papers that detect leaf diseases with deep learning methods are analyzed. The primary search keywords examined in this review are leaf diseases, deep learning, detection, classification, and algorithm. The synonyms belonging to each principle term were characterized. OR and AND Boolean operators were utilized in our search criteria. Significantly, search engines can restore correlations for leaf disease detection and classification.

C. LITERATURE REVIEW SEARCH SELECTION CRITERIA

The search selection criteria display how we refine related articles retrieved from search engines. Our goal is to identify primary articles related to our topic that answer our research questions. A total of 256 studies were selected from various databases. Articles published between 2006 and 2022 were included in the study analysis (Figure 2). We had to exclude many irrelevant papers unrelated and duplicated to the research criteria. A total of seven electronic databases were used to select research studies for the procedure. Figure 1 shows the seven electronic databases and the number of papers selected from each database. The papers were categorized into three groups: articles, conferences, and workshops. Google Scholar has the most articles with the attention of 23.82% (61), and Science Direct came next with the attention of 17.18% (44). IEEE Xplore takes the lead for conference papers with the attention of 30.85% (79) while 26.56 % (68) of articles and conference papers are distributed between the other databases. There are four workshop papers, Google Scholar and IEEE Xplore with the attention of 1.17% (3), and 0.39% (1) respectively. Figure1 below shows the electronic databases.

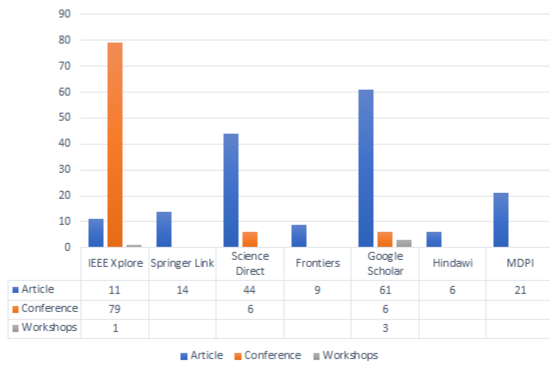

FIGURE 1. Research studies on electronic databases.

D. PRISMA FLOW DIAGRAM

This literature review uses the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram, a research-based practice, to depict the review. The authors utilize the PRISMA flow diagram to enhance overall paper selection and improve the quality of the literature review [24]. Refer to the below Figure 2. This literature review covers only papers written in English that pertain to the detection and classification of leaf diseases through deep learning, machine learning, and other methods [25]. For this literature review, only English papers published in 2006 or later and not duplicates have been chosen. Any paper that does not meet these criteria will be excluded [26]. The chosen studies are identified following these steps:

1) IDENTIFICATION

The diagram begins with an initial number of records found through various analysis methods, including manual queries,

TABLE 1. Description of the research questions.

RQ1: Which machine/deep learning algorithms have been used to detect leaf diseases?	Study and evaluate the algorithms utilized in leaf disease detection	Machine/deep learning algorithms
RQ2: Which machine/deep learning architectures have been used to detect leaf diseases?	Recognize the architectures used in leaf disease detection and classification	Machine/deep learning architectures
RQ3: Which databases have been used to detect leaf diseases?	Discover the database where the dataset was collected and the number of images	Name of the databases
RQ4: What type of plant leaf diseases and plants have been examined?	Determine the disease types and yields that are most infected	Leaf diseases
RQ5: What types of procedures and frameworks have been used?	Determine the approaches used to classify and detect diseases	Techniques and highest and lowest accuracy
RQ6: Who are the authors and publishers?	Locate the website name where the research was published and the authors' names	Research studies
RQ7: What are the advantages and disadvantages of procedures and frameworks?	Identify the pros and cons of each type of procedure and framework	Advantages and disadvantages

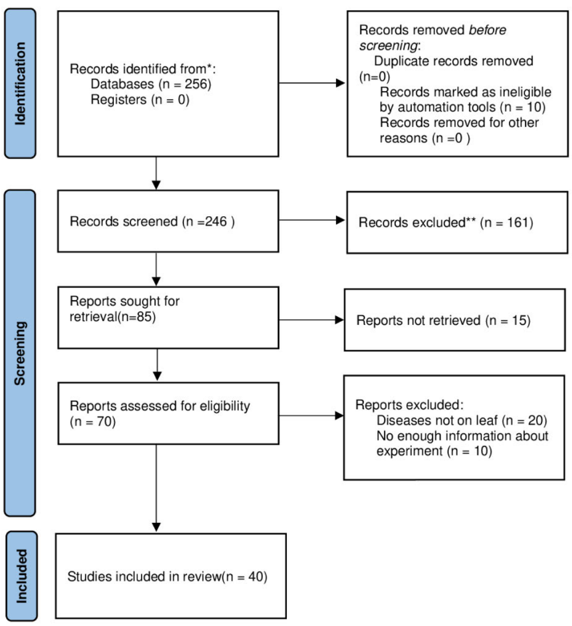

FIGURE 2. PRISMA flow diagram.

literature databases, etc. Therefore, articles were chosen from different databases, including Google Scholar, IEEE, Springer Link, Science Direct, Frontiers in Plant Science, Hindawi, and MDPI. A total of 256 articles that are relevant to the topic were selected.

2) SCREENING

After removing duplicates, it displays the number of records remaining. Titles and abstracts of the retrieved records are screened to determine their relevance to the study subject. Duplicate articles and papers were taken out. Following the screening process, ten journal articles were ineligible for inclusion.

3) ELIGIBILITY

The overall number of research papers that advanced to the next level after passing the first round of screening is shown in the flow diagram. The full-text publications of potentially relevant studies are then evaluated against the criteria established for eligibility. Therefore, we scanned and analyzed eighty-five research papers to determine the outcomes. We excluded one hundred and sixty-one studies for their irrelevance or lack of relevance to the research questions and discussion.

4) INCLUDED/EXCLUSION

It lists the total number of research papers that were part of our comprehensive review. These papers are deemed appropriate for further investigation because they satisfy the predetermined eligibility requirements. The flow graphic shows how many studies were omitted at each stage as well as the reasons for those exclusions. Lack of relevance to the research issue, a poor study design, lack of information, or an inability to meet particular requirements for inclusion are all frequent grounds for exclusion. However, this systematic review was supported by forty studies.

E. DATA EXTRACTION

We organized the papers into two categories: articles and conference papers. The process is to examine each paper and organize them by publication year. This data extraction generates a list of research studies and evidence to answer research questions. This study examines research studies conducted between 2006 and 2022. In terms of detecting and classifying leaf diseases, 2019 was a milestone year. Figure 3 shows the growth of research studies during this period. At the termination of the composition activities, Table 9 was

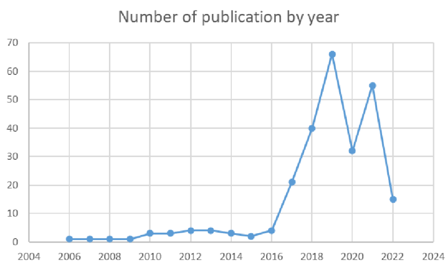

FIGURE 3. Number of publications from the year 2006 to 2022.

TABLE 2. Prevalent approximation of 256 studies.

Type of Algorithm	Number	Percentage
Deep Learning	213	83.20%
Machine Learning	24	9.50%
Traditional Algorithms	10	3.90%
Machine and Deep Learning	9	3.50%

intended to be available in the extension, with 40 research studies selected for extraction. Ultimately, the table consists of the following attributes: article (author's name), year (published year), plant (name of the plant), number of images (number of images), dataset (location of the data), framework, model or algorithm (the algorithm used in the experiment), architecture (the architecture utilized), and best accuracy.

IV. RESULTS

We discuss 40 studies out of 256 studies in this section that contributed to the answer to our research questions.

A. RQ1: WHICH MACHINE/DEEP LEARNING ALGORITHMS HAVE BEEN USED TO DETECT LEAF DISEASES?

RQ1 is intended to discuss which machine learning and deep learning algorithms have been utilized to classify and detect leaf diseases. Based on our findings from the research studies, we found the most common algorithms to be Convolutional Neural Networks (CNN), support vector machines (SVM), artificial neural networks (ANN), and deep neural networks (DNN). We realized that a Convolutional Neural Network (CNN) is a widely used algorithm. There is a lot of interest in deep learning, around 83.20%. There were around 9.50% of machine learning algorithms in the following categories. Around 7.40% of the research studies were devoted to machine/deep learning algorithms and traditional algorithms combined. Additionally, some studies used machine learning and deep learning algorithms to achieve better accuracy and compare model performance. For instance, Hasan et al. [27] used CNN, SVM, KNN, and RF algorithms in Jute plant diseases. Table 2 shows the prevalent 256 studies.

TABLE 3. Deep learning architectures.

Architectures	No of articles	Percentage
ResNet	5	12.50%
EfficientNet	3	7.50%
VGGNet	2	5.00%
AlexNet	2	5.00%
LeNet	2	5.00%
GoogLeNet	2	5.00%
YoloV	2	5.00%
MobileNet	1	2.50%
Inception	1	2.50%
Other	25	62.50%

TABLE 4. Classification and detection example.

Model	Plant	Accuracy
ResNet	Tomato	97.28%
EfficientNetB7	Apple	99.80%
VGGNet	Grape	98.40%
AlexNet	Cucumber	94.27%
LeNet	Banana	65.93%
GoogLeNet	Pomelo	82.70%
YoloV5	Potato	99.75%
MobileNet	Multiple	98.65%
InceptionV3	Rice	99.33%

TABLE 5. Pros and cons of different architectures.

Architecture	Pros	Cons
ResNet	Improves the efficiency	Complexity
	minimizing errors	Requires more memory
EfficientNet	Improve performance	Many computational resources
	Fewer parameters	perform poorly on hardware
VGGNet	Fewer parameters	long training time
	Smaller kernels	large model size
AlexNet	Breakthrough performance	Complexity
	Faster training	Overfitting
LeNet	Simplicity	Overfitting
	Easy to use	Lack of interpretability
GoogLeNet	Faster	Large number of parameters
	Smaller size	Overfitting

B. RQ2: WHICH MACHINE/DEEP LEARNING ARCHITECTURES HAVE BEEN USED TO DETECT LEAF DISEASES?

RQ2 evaluates machine learning and deep learning architectures for leaf disease detection and classification. Table 3 shows the research studies containing different Deep Learning (DL) architectures used in the selected papers. The gathered information indicates that deep learning was the most used with 65% (26), and other architectures received 35(14)%, respectively. Deep learning architectures such as VGG, AlexNet, LeNet, InceptionV, and others were widely used in selected research studies. In addition, multiple research studies utilized different deep learning architectures in training and testing datasets. Table 4 displays classification and detection examples of different models. Deep learning has different architectures that have been used in leaf disease classification and detection. Table 5 shows the comparison of different deep learning architectures.

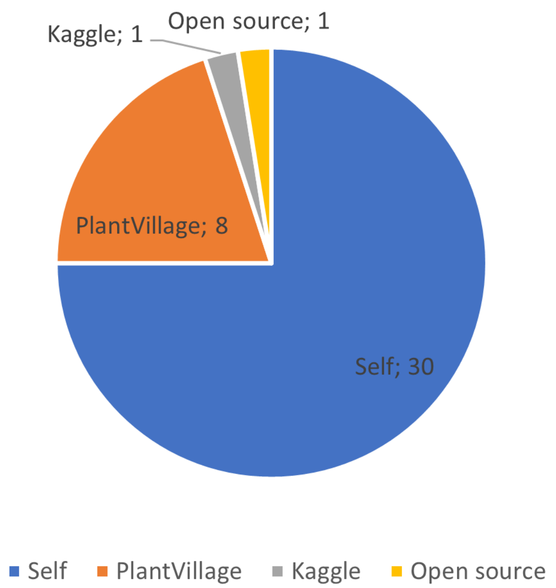

FIGURE 4. Data sources.

C. RQ3: WHICH DATABASES HAVE BEEN USED TO DETECT LEAF DISEASES?

RQ3 concerns where the data is collected from and the databases' names. Images collected from the field (Self) are the most used in the research studies receiving 75% (30), followed by PlantVillage at 20% (8). In comparison, the Kaggle dataset reached 2.50% (1), and open-source and other databases 2.50% (1), respectively. According to the investigations of the research studies, most studies utilized a digital camera and mobile phone to capture images from the field. Figure 4 shows the database sources.

D. RQ4: WHAT TYPE OF PLANT LEAF DISEASES AND PLANTS HAVE BEEN EXAMINED?

In RQ4, the main goal is to discover the most common leaf type in the literature review. Figure 5 categorizes the surveyed yields in research studies into multiple kinds of vegetables, fruits, and flowers.

Our results show that fruits are dominant in the survey. The total number of crops is 40; multiple pieces are the most dominant plant, 12.5% (5). Apple and corn are the second, with a share of about 20 % (8). Cotton and cucumber come next with a share of about 15% (6). The other crops receive less attention than the aforementioned plants, 52.5% (21).

E. RQ5: WHAT TYPES OF PROCEDURES AND FRAMEWORKS HAVE BEEN USED?

Specifically, RQ5 analyzes the contributions of research studies according to their techniques and frameworks. We discovered multiple frameworks commonly used in traditional and machine learning by examining research studies. Figure 6 shows the techniques and frameworks used in research studies. It is clear that Matlab is the most framework used to classify leaf diseases with a focus of 27.5% (11). The TensorFlow framework comes in second with 15% (6). In the third position are the PyTorch and Cafe frameworks together with 25% (10). TensorFlow with Keras with 7.5% (3). Python framework attention is 5% (2).

F. RQ6: WHO ARE THE AUTHORS AND PUBLISHERS?

Research studies are classified according to publishers and types (articles/conferences) in RQ6. The research studies were selected from 2006 to 2022, with articles related to leaf diseases. Figures 1 and 3 categorize and classify publications by year. The year 2019 has the most published papers with 26.29% (66), followed by 2021 with 21.48% (55) papers. The year 2018 came next with 15.62% (40), followed by 2020 with 12.5% (32). While from 2006 to 2009, the number of papers decreased by 0.39% (1) respectively.

G. RQ7: WHAT ARE THE ADVANTAGES AND DISADVANTAGES OF PROCEDURES AND FRAMEWORKS?

We examine some significant issues that come up when creating neural network applications. Our goal is to discover whether the selection of a library can affect the system's overall performance, either during training or design and to derive a set of standards that might be utilized to demonstrate the benefits and drawbacks of each library under study [28]. Table 6 displays the advantages and disadvantages of procedures and frameworks.

TABLE 6. Advantages and disadvantages of procedures and frameworks.

Framework	Advantages	Disadvantages
Matlab	Ease to use	Cost
	Platform independence	Interrupted language
TensorFlow	Scalability	Process slow
	Flexibility	Missing Symbolic Loops
Caffe	Fast	Is not flexible
	Open source	Limited community
PyTorch	Flexibility	Low-level API
	Easier to debug	limited support
Keras	Simplicity	Inefficient errors
	Backend support	Low-level API
Python	Ease to read	Slow speed
	Vast libraries support	Runtime errors

V. DISCUSSION

Our literature is organized into four main points on leaf disease using deep learning, machine learning, and other architectures. In this section, we will discuss the following points in detail.

A. TRADITIONAL AND MACHINE LEARNING APPROACHES

Several architectures have been proposed for the detection and classification of leaf diseases. Traditional architectures, such as texture features based on color co-occurrence methods, are widely used to detect leaf diseases [29]. Fuzzy feature approaches can significantly enhance leaf disease diagnosis. This approach uses the mean square error (MSE) to estimate the performance [30]. Meunkaewjinda et al. [31]

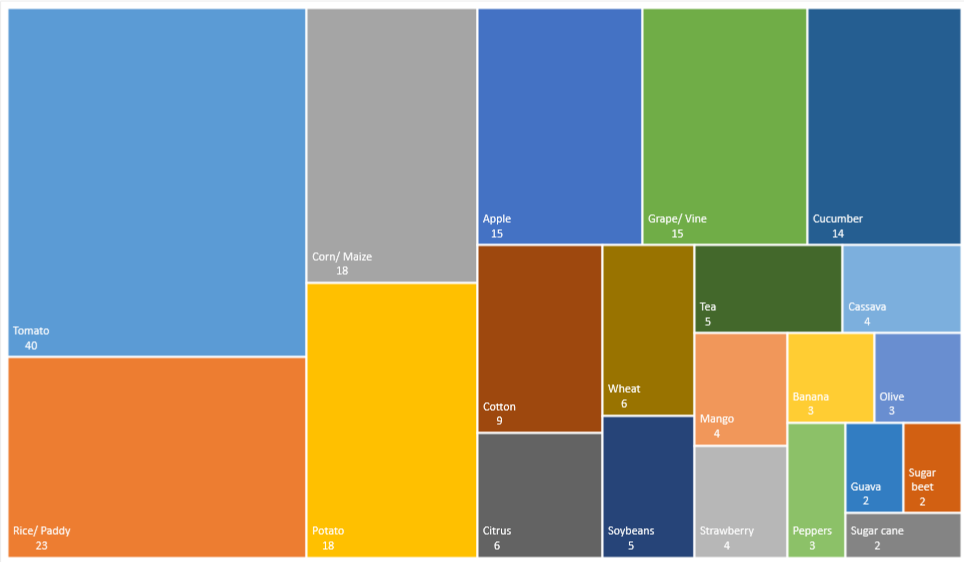

FIGURE 5. Type of plant leaf diseases.

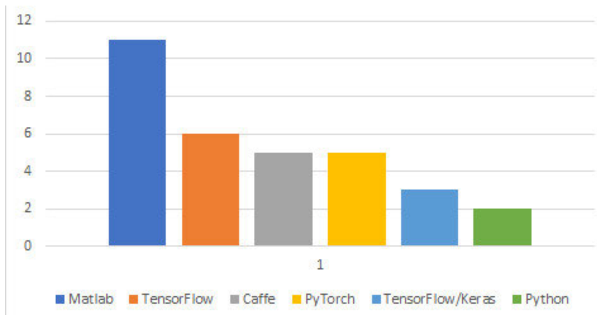

FIGURE 6. Most relevant frameworks used in the research studies.

TABLE 7. Highest and lowest accuracy for apple plant diseases.

Plant	Architecture	Ref.#	Highest Accu.	Lowest Accu.
Apple	VGG16	[34]	90.40%	80.00%
	AlexNet	[35]	97.62%	86.79%
	VGG	[36]	85.00%	63.23%
	FCNN-LDA	[37]	90.00%	89.50%
	VGG	[38]	84.30%	74.70%
	YOLOV3/DenseNet	[12]	95.57%	93.84%
	SegNet/GANs	[39]	64.30%	52.90%
	XDNet	[40]	98.82%	96.29%
	CNN	[1]	96.25%	90.00%
	ResNet-50	[41]	99.00%	98.74%
	EfficientNetB7	[42]	91.46%	63.35%
	CNN	[43]	99.20%	87.20%

proposed a technique employing a self-organizing feature map based on a back-propagation neural network to diagnose grape diseases. SVM, Bayesian, and K-nearest classifiers are utilized in plant disease diagnosis [32].

B. DEEP LEARNING ALGORITHMS

Since 2012, the state-of-the-art Convolution Neural Network (CNN) has been used widely in different domains, especially plant diseases, and pets, to decrease crop loss [33]. Several algorithms in this research study provide reliable solutions to leaf diseases.

RQ2 indicates that the ResNet architecture is most commonly utilized in the investigated studies, followed by EfficientNet and AlexNet. Other deep learning architectures, such as VGG, Faster R-CNN, and Yolo-V3, significantly improved plant disease detection and classification [12]. Generally, most CNN architectures such as VGGNet, AlexNet, and ResNet share categories like the number of parameters, optimizers, hyperparameters, and the number of layers. According to the analysis of the research studies examination, the use of architecture for leaf diseases varies depending on the plant type and the architecture used. One architecture works better for one plant disease and provides better accuracy results while not working well for another. Therefore, several procedures and steps must be taken into consideration to obtain more accurate results, including overfitting issues, the number of hyperparameters, and the number of layers.

C. WHICH ARCHITECTURE PRODUCED THE HIGHEST AND LOWEST ACCURACY?

Table 7 shows the extracted information on the architecture with the highest accuracy for apple plants. The table shows different studies that utilized various architectures and obtained different accuracy results for apple plants. The analysis revealed that the accuracy of the architectures varies. However, compared to the other architectures, the CNN architecture has the highest accuracy of 99.2%, while the SegNet/GANs architecture has the lowest accuracy of 64.3%.

TABLE 8. Feature extraction for CNN algorithm.

Algorithm	Feature extraction	Ref.#	Plant	Accuracy
Convolutional Neural Network (CNN)	VGG	[45]	Cucumber	82.30%
	InceptionV3	[46]	Cassava	93.00%
	LeNet	[8]	Banana	99.72%
	VGG16	[34]	Apple	90.40%
	Faster-RCNN	[47]	Corn	95.00%
	ResNet	[48]	Wheat	96.00%
	SegNet/GANs	[39]	64.3%	52.90%
	ResNet-101	[49]	Tomato	98.80%
	ImageNet	[50]	Apple/Tomato	87.00%
	GoogLeNet	[11]	Cherry	99.60%
	ResNet	[51]	Corn	99.79%
	AlexNet	[52]	Olive	99.11%
	DCNN	[53]	Corn	88.46%
	ResNet-101	[54]	Maize	91.83%
	ResNet-50	[55]	Peanut	97.59%
	EfficientNet	[56]	Cassava	87.00%
	GoogLeNet	[57]	Pomelo	82.70%
	YoloV5	[58]	Sweet cherry	86.10%
	EfficientNetB2	[59]	Cardamom	98.26%
	EfficientNetB7	[60]	Grape	98.70%

D. WHAT ARE THE MOST USED FEATURE EXTRACTIONS IN CONVOLUTIONAL NEURAL NETWORK (CNN) FOR LEAF DISEASE DETECTION AND CLASSIFICATION?

Feature extraction is crucial for algorithms used in the classification and detection of leaf diseases. It is a significant aspect of machine learning and image pattern classification. Feature extraction enhances the processing performance while minimizing redundancy and preserving the relevant information. Features with the highest accuracy score are selected for recognition. Some algorithms do not require feature extraction, as discussed in [25] and [44]. Table 8 presents the feature extractions with the highest accuracy, used in conjunction with the CNN algorithm. It was determined that ResNet yielded the highest accuracy compared to other CNN features.

E. DATABASES AND DATA-SETS CHARACTERISTICS

Multiple characteristics influence the datasets: the number of images collected for training and testing, disease types, pet type, and disease factors. Image preparation and adjustment play an essential role in results accuracy. The reply to the question RQ3 categorizes the dataset with the highest repetition in research studies. We noticed that 75% of the papers collected their dataset from the field (Self). The plant village dataset came next with an accuracy of 20%. In Table 9 we categorized the type of dataset into (images collected from the field (Self), plant village, Kaggle, open-source, and other databases) that form the datasets. According to the results, digital cameras, unmanned aerial vehicles (UAV), and smartphones were the most commonly used devices to capture field images. Besides, as mentioned earlier, different other databases offer images for training and testing, such as AI Challenger and other databases.

F. TYPES OF PLANTS AND DISEASES

The research studies were applied to different vegetables and fruits using different methods and algorithms. RQ4 discussed a variety of plants. The majority of research studies focused on vegetables and fruits. Most studies focused on leaf diseases such as tomato, rice, potato, corn, grape, and apple plants. Wang et al. [61] discussed tomato disease. For instance, malformed tomato, puffy tomato, tomato virus disease, and other tomato diseases were researched in this paper. Irmak and Saygili [62] researched tomato leaf diseases such as Septoria leaf spot, yellow leaf curl, and bacterial spot.

G. TECHNIQUES AND FRAMEWORKS

Methods and frameworks play a critical role in study accuracy. RQ 5 points out that the Matlab framework is the most favored, with 27.5%. The TensorFlow framework is also considered useful and utilized with a concern of 15%, followed by Caffe and PyTorch frameworks with concerns of 25%. Matlab is primarily used as a framework in traditional machine-learning studies. Various frameworks were used for deep learning architectures, including TensorFlow, Keras, and Caffe. TensorFlow is considered to be the most reliable framework for detecting and classifying plant leaf diseases in most research studies.

VI. FUTURE RESEARCH PROSPECT AND POSSIBLE SOLUTION FOR LIMITATIONS

Processing leaf images in plants is rapidly spreading throughout the industry, as replicating human visual talents is a critical first step in the automation of operations. The development of a computer vision system for disease diagnosis. The subsequent next-generation characteristics can be taken into consideration for additional research according to our major results from the prior investigations [63].

a) In the future, the current algorithms can be used in natural environments and integrated with leaf fronts as well as leaf backs into a single dataset.

b) The automatic assessment of the severity of the identified problems may also be the focus of future research.

c) By creating sophisticated algorithms, current research can also be expanded to attain greater speed as well as accuracy.

In the present article, numerous ways of recognizing, and predicting leaf diseases utilizing image and classification methods are developed and put into practice. The paper provides an overview of the technical terms used in the current approaches that are relevant to the research's goal. The classification and detection of leaf diseases is a field of study that goes beyond the previously discussed potential future applications. The goal of this work was to list and explain some of the major obstacles that still need to be removed before an image-based diagnosis system that is actually effective is made available [64].

Placing restrictions to restrict the fluctuations in capture conditions could be one method to get around some of the constraints that still exist for this kind of technology. The additional work needed to meet those limits may discourage many potential users from utilizing the technology, which is an unfavorable side effect of the method.

TABLE 9. Summary of the study characteristics.

Article	Year	Plant	No: of image	Dataset	Framework	Algorithm	Architecture	Best accuracy
[26]	2006	Citrus	160	Self	Matlab	Color texture features	CCM	95.00%
[30]	2007	Cotton	150	Self	N/A	FC/FS	MSE	—
[31]	2008	Grape	410	Self	N/A	SVM	N/A	86.03%
[32]	2009	Rice	216	Self	Visual C++	SVM	N/A	97.20%
[65]	2010	Cucumber	336	Self	N/A	SVM	EBF Kernel	91.70%
[66]	2010	Soybean	32	Self	N/A	RIA/RCI	N/A	87.00%
[67]	2011	Cotton	40	Self	Matlab	SVM and ANN	SVM	91.00%
[68]	2011	Multiple	192	Self	Matlab	NN/K-means	N/A	94.00%
[69]	2012	Cotton	N/A	Self	N/A	BP NN	N/A	89.50%
[70]	2012	Wheat	114	Self	N/A	MLR and PLSR	N/A	90.00%
[71]	2013	Multiple	192	Self	Matlab	Otus's method	N/A	94.00%
[72]	2013	Multiple	2616	Plant pathology	Matlab	DWT and PCA	MDC/PNN	86.48%
[73]	2014	Multiple	600	Plant Pathology	Matlab	ANN/Kn-Based	c-texture/c-features	94.30%
[73]	2014	Multiple	990	Self	Matlab	BPNN	N-KNN/ANN	91.54%
[74]	2015	Multiple	N/A	Plant pathology	Matlab	ANN/N-neighbor	GLCM and GLRM	94.85%
[45]	2016	Cucumber	7,520	Self	Caffe	CNN	VGG	82.30%
[46]	2017	Cassava	11,670	Self	TensorFlow	CNN	InceptionV3	93.00%
[8]	2017	Banana	3,700	Self	Matlab	CNN	LeNet	99.72%
[34]	2017	Apple	2,086	Plant village	Theano	CNN	VGG16	90.40%
[75]	2018	Soybeans	25,000	Self	PyTorch	DCNN	PLNet and LeNet	94.13%
[47]	2018	Corn	10,784	Self	Caffe	CNN	Faster R-CNN	95.00%
[76]	2018	Cucumber	14,208	Self	Matlab	DCNN	AlexNet	93.40%
[48]	2018	Wheat	8,178	Self	TensorFlow	CNN	ResNet	96.00%
[49]	2019	Tomato	6,888	Plant village	Matlab	CNN	ResNet-101	98.80%
[50]	2019	Apple and tomato	3663	Plant village	TensorFlow	CNN	ImageNet	87.00%
[77]	2019	Blueberry	800	Self	Python	Deep learning	CNN	84.00%
[11]	2019	Cherry	1,200	Self	Python	CNN	GoogLeNet	99.60%
[12]	2019	Apple	640	Self	TensorFlow	DNN	YOLOV3/DenseNet	95.75%
[51]	2019	Corn	15,240	Self	TensorFlow	CNN	ResNet/crowdsourced	99.79%
[52]	2019	Olive	54,306	Plant village	TensorFlow	CNN	AlexNet	99.11%
[53]	2020	Corn	679	Self	TensorFlow/ Keras	CNN	Deep CNN	88.46%
[78]	2020	Tomato	14,072	Self	Caffe/DarkNet53	MobileNetV2	"MobileNetV2/YOL3"	86.98%
[40]	2020	Apple	2,979	Self	Keras	D-CNN	XDNet	98.82%
[54]	2020	Maize	8,152	NLB	Caffe	CNN	ResNet-101	91.83%
[55]	2021	Peanut	6,029	Self	PyTorch	CNN	ResNet50	97.59%
[56]	2021	Cassava	10.839	Kaggle	TensorFlow/ Keras	CNN	EfficientNet	87.00%
[57]	2021	Pomelo	540	Self	Caffe	CNN	GoogLeNet	82.70%
[58]	2021	Sweet cherry	11,676	Self	Yolov5	CNN	YOLOV5	86.10%
[59]	2022	Cardamom	1,724	Self	PyTorch	CNN	EfficientNetB2	98.26%
[60]	2022	Grape	9,027	Plant village	TensorFlow/ Keras	CNN	EfficientNetB7	98.70%

The application of more advanced methods taken from the fields of computer vision and machine learning may be able to reduce some of the major problems such as graph theory, mean shift, and other problems that have not yet been examined.

A lot of issues still need to be resolved in the extremely difficult scientific field of computer-assisted plant disease detection [33]. There is no doubt that technology will advance to produce more advanced instruments, but given the complexity of the situation, it is unlikely that plant pathologists or other plant science experts will be substituted.

VII. CONCLUSION

This study explores distinguishing and demonstrating the prevalent literature on machine learning for leaf disease detection and classification. We conducted a methodical mapping survey to evaluate six research questions. In this study, we sorted out 256 research studies from seven databases. A notable advantage of the study is the development and implementation of a system for classifying and detecting leaf diseases in the early stages. Classifying and detecting leaf diseases at early stages will encourage farmers to take the necessary precautions to reduce yield loss. Our study reveals that CNN is extensively used in various studies. Machine learning methods identify problems and difficulties in plant disease diagnosis and classification. For instance, data representation, labeling, and collection are the main challenges facing machine learning development. Overfitting is one of the existing problems in machine learning and deep learning. Our study shows considerable progress in using deep learning architectures for plant disease classification and detection. Traditional machine-learning algorithms and the difficulties of capturing image data sets of leaves in the field affect the models' performance. Diseases are developing and rising based on field observation. However, optimization and customization processes still need to address many problems and gaps. The majority of studies have utilized CNN approaches, according to our research. We discovered that most CNN approaches have numerous problems and challenges. The inadequacy of datasets constitutes one of the greatest challenges researchers encounter when conducting their studies. Developing highly effective detection methods based on large databases of leaf diseases will have a major impact in the future. This will also alleviate the class imbalance problem by requiring significantly generalized datasets. Lastly, this study considers the background for more advanced plant disease detection and classification research. Farmers can increase productivity by improving crop disease diagnosis and prediction and avoiding economic damage.

REFERENCES

[1] P. Bansal, R. Kumar, and S. Kumar, "Disease detection in apple leaves using deep convolutional neural network," *Agriculture*, vol. 11, no. 7, p. 617, Jun. 2021.

[2] Y. Yuan, S. Fang, and L. Chen, "Crop disease image classification based on transfer learning with DCNNs," in *Pattern Recognition and Computer Vision*. Cham, Switzerland: Springer, 2018, pp. 457–468.

[3] R. S. Latha, G. R. Sreekanth, R. C. Suganthe, R. Rajadevi, S. Karthikeyan, S. Kanivel, and B. Inbaraj, "Automatic detection of tea leaf diseases using deep convolution neural network," in *Proc. Int. Conf. Comput. Commun. Informat. (ICCCI)*, Jan. 2021, pp. 1–6.

[4] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," *Comput. Intell. Neurosci.*, vol. 2016, pp. 1–11, Jan. 2016.

[5] P. Goncharov, G. Ososkov, A. Nechaevskiy, A. Uzhinskiy, and I. Nestsiarenia, "Disease detection on the plant leaves by deep learning," in *Proc. Int. Conf. Neuroinform.*, 2018, pp. 151–159.

[6] S. Ramesh, R. Hebbar, M. Niveditha, R. Pooja, N. Shashank, and P. V. Vinod, "Plant disease detection using machine learning," in *Proc. Int. Conf. Design Innov. 3Cs Compute Communicate Control (ICDI3C)*, Apr. 2018, pp. 41–45.

[7] V. Malathi and M. P. Gopinath, "Classification of pest detection in paddy crop based on transfer learning approach," *Acta Agriculturae Scandinavica, B—Soil Plant Sci.*, vol. 71, no. 7, pp. 552–559, Oct. 2021.

[8] J. Amara, B. Bouaziz, and A. Algergawy, "A deep learning-based approach for banana leaf diseases classification," in *Proc. Datenbanksysteme Business, Technologie Web-Workshopband*, 2017, pp. 79–88.

[9] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, "Identification of plant-leaf diseases using CNN and transfer-learning approach," *Electronics*, vol. 10, no. 12, p. 1388, Jun. 2021.

[10] K. Zhang, Q. Wu, A. Liu, and X. Meng, "Can deep learning identify tomato leaf disease?" *Adv. Multimedia*, vol. 2018, pp. 1–10, Sep. 2018.

[11] K. Zhang, L. Zhang, and Q. Wu, "Identification of cherry leaf disease infected by Podosphaera pannosa via convolutional neural network," *Int. J. Agricult. Environ. Inf. Syst.*, vol. 10, no. 2, pp. 98–110, Apr. 2019.

[12] Y. Tian, G. Yang, Z. Wang, E. Li, and Z. Liang, "Detection of apple lesions in orchards based on deep learning methods of CycleGAN and YOLOV3-dense," *J. Sensors*, vol. 2019, pp. 1–13, Apr. 2019.

[13] H. Durmus, E. O. Günes, and M. Kirci, "Disease detection on the leaves of the tomato plants by using deep learning," in *Proc. 6th Int. Conf. Agro-Geoinformatics*, Aug. 2017, pp. 1–5.

[14] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers Plant Sci.*, vol. 7, p. 1419, Sep. 2016.

[15] V. Bischoff, K. Farias, J. P. Menzen, and G. Pessin, "Technological support for detection and prediction of plant diseases: A systematic mapping study," *Comput. Electron. Agricult.*, vol. 181, Feb. 2021, Art. no. 105922.

[16] A. Abade, P. A. Ferreira, and F. de Barros Vidal, "Plant diseases recognition on images using convolutional neural networks: A systematic review," *Comput. Electron. Agricult.*, vol. 185, Jun. 2021, Art. no. 106125.

[17] M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant disease detection and classification by deep learning," *Plants*, vol. 8, no. 11, p. 468, 2019.

[18] W. Albattah, M. Nawaz, A. Javed, M. Masood, and S. Albahli, "A novel deep learning method for detection and classification of plant diseases," *Complex Intell. Syst.*, vol. 8, pp. 1–18, Sep. 2022.

[19] H. A. Atabay, "Deep residual learning for tomato plant leaf disease identification," *J. Theor. Appl. Inf. Technol.*, vol. 95, no. 24, pp. 1–12, 2017.

[20] M. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: Classification and symptoms visualization," *Appl. Artif. Intell.*, vol. 31, no. 4, pp. 299–315, Apr. 2017.

[21] S. Barburiceanu, S. Meza, B. Orza, R. Malutan, and R. Terebes, "Convolutional neural networks for texture feature extraction. Applications to leaf disease classification in precision agriculture," *IEEE Access*, vol. 9, pp. 160085–160103, 2021.

[22] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks," *Artif. Intell. Rev.*, vol. 53, no. 8, pp. 5455–5516, Dec. 2020.

[23] Z. B. Husin, A. Y. B. Md. Shakaff, A. H. B. A. Aziz, and R. B. S. M. Farook, "Feasibility study on plant chili disease detection using image processing techniques," in *Proc. 3rd Int. Conf. Intell. Syst. Modeling Simulation*, Feb. 2012, pp. 291–296.

[24] O. O. Sumady, B. J. Antoni, R. Nasuta, and E. Irwansyah, "A review of optical text recognition from distorted scene image," in *Proc. 4th Int. Conf. Cybern. Intell. Syst. (ICORIS)*, Oct. 2022, pp. 1–5.

[25] E. A. Soelistio, R. E. Hananto Kusumo, Z. V. Martan, and E. Irwansyah, "A review of signature recognition using machine learning," in *Proc. 1st Int. Conf. Comput. Sci. Artif. Intell. (ICCSAI)*, vol. 1, Oct. 2021, pp. 219–223.

[26] A. R. Anik, K. Hasan, M. M. Islam, M. M. Hasan, M. F. Ali, and S. K. Das, "Non-invasive portable technologies for monitoring breast cancer related lymphedema to facilitate telehealth: A scoping review," *IEEE J. Biomed. Health Informat.*, vol. 27, no. 9, pp. 4524–4535, Sep. 2023.

[27] Md. Z. Hasan, Md. S. Ahamed, A. Rakshit, and K. M. Z. Hasan, "Recognition of jute diseases by leaf image classification using convolutional neural network," in *Proc. 10th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Jul. 2019, pp. 1–5.

[28] O.-C. Novac, M. C. Chirodea, C. M. Novac, N. Bizon, M. Oproescu, O. P. Stan, and C. E. Gordan, "Analysis of the application efficiency of TensorFlow and PyTorch in convolutional neural network," *Sensors*, vol. 22, no. 22, p. 8872, Nov. 2022.

[29] R. Pydipati, T. F. Burks, and W. S. Lee, "Identification of citrus disease using color texture features and discriminant analysis," *Comput. Electron. Agricult.*, vol. 52, nos. 1–2, pp. 49–59, Jun. 2006.

[30] Y.-C. Zhang, H.-P. Mao, B. Hu, and M.-X. Li, "Features selection of cotton disease leaves image based on fuzzy feature selection techniques," in *Proc. Int. Conf. Wavelet Anal. Pattern Recognit.*, vol. 1, Nov. 2007, pp. 124–129.

[31] A. Meunkaewjinda, P. Kumsawat, K. Attakitmongcol, and A. Srikaew, "Grape leaf disease detection from color imagery using hybrid intelligent system," in *Proc. 5th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol.*, vol. 1, May 2008, pp. 513–516.

[32] Q. Yao, Z. Guan, Y. Zhou, J. Tang, Y. Hu, and B. Yang, "Application of support vector machine for detecting rice diseases using shape and color texture features," in *Proc. Int. Conf. Eng. Comput.*, May 2009, pp. 79–83.

[33] A. Fuentes, S. Yoon, S. Kim, and D. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," *Sensors*, vol. 17, no. 9, p. 2022, Sep. 2017.

[34] G. Wang, Y. Sun, and J. Wang, "Automatic image-based plant disease severity estimation using deep learning," *Comput. Intell. Neurosci.*, vol. 2017, pp. 1–8, Jan. 2017.

[35] B. Liu, Y. Zhang, D. He, and Y. Li, "Identification of apple leaf diseases based on deep convolutional neural networks," *Symmetry*, vol. 10, no. 1, p. 11, Dec. 2017.

[36] K. Park, Y. K. Hong, G. H. Kim, and J. Lee, "Classification of apple leaf conditions in hyper-spectral images for diagnosis of *Marssonina* blotch using mRMR and deep neural network," *Comput. Electron. Agricult.*, vol. 148, pp. 179–187, May 2018.

[37] M. Agarwal, R. K. Kaliyar, G. Singal, and S. K. Gupta, "FCNN-LDA: A faster convolution neural network model for leaf disease identification on apple's leaf dataset," in *Proc. 12th Int. Conf. Inf. Commun. Technol. Syst. (ICTS)*, Jul. 2019, pp. 246–251.

[38] H.-J. Yu and C.-H. Son, "Apple leaf disease identification through region-of-interest-aware deep convolutional neural network," 2019, *arXiv:1903.10356*.

[39] C. Douarre, C. F. Crispim-Junior, A. Gelibert, L. Tougne, and D. Rousseau, "Novel data augmentation strategies to boost supervised segmentation of plant disease," *Comput. Electron. Agricult.*, vol. 165, Oct. 2019, Art. no. 104967.

[40] X. Chao, G. Sun, H. Zhao, M. Li, and D. He, "Identification of apple tree leaf diseases based on deep learning models," *Symmetry*, vol. 12, no. 7, p. 1065, Jun. 2020.

[41] C. Zhou and J. Xing, "Improved deep residual network for apple leaf disease identification," *J. Inf. Process. Syst.*, vol. 17, no. 6, pp. 1–10, 2021.

[42] S. Divakar, A. Bhattacharjee, and R. Priyadarshini, "Smote-DL: A deep learning based plant disease detection method," in *Proc. 6th Int. Conf. Converg. Technol. (I2CT)*, Apr. 2021, pp. 1–6.

[43] D.-J. Jwo and S.-F. Chiu, "Deep learning based automated detection of diseases from apple leaf images," *Comput., Mater. Continua*, vol. 71, no. 1, pp. 1849–1866, 2022.

[44] M. Sharif, M. A. Khan, Z. Iqbal, M. F. Azam, M. I. U. Lali, and M. Y. Javed, "Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection," *Comput. Electron. Agricult.*, vol. 150, pp. 220–234, Jul. 2018.

[45] E. Fujita, Y. Kawasaki, H. Uga, S. Kagiwada, and H. Iyatomi, "Basic investigation on a robust and practical plant diagnostic system," in *Proc. 15th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2016, pp. 989–992.

[46] A. Ramcharan, K. Baranowski, P. McCloskey, B. Ahmed, J. Legg, and D. P. Hughes, "Deep learning for image-based cassava disease detection," *Frontiers Plant Sci.*, vol. 8, p. 1852, Oct. 2017.

[47] S. Jin, Y. Su, S. Gao, F. Wu, T. Hu, J. Liu, W. Li, D. Wang, S. Chen, Y. Jiang, S. Pang, and Q. Guo, "Deep learning: Individual maize segmentation from terrestrial LiDAR data using faster R-CNN and regional growth algorithms," *Frontiers Plant Sci.*, vol. 9, p. 866, Jun. 2018.

[48] A. Picon, M. Seitz, A. Alvarez-Gila, P. Mohnke, A. Ortiz-Barredo, and J. Echazarra, "Crop conditional convolutional neural networks for massive multi-crop plant disease classification over cell phone acquired images taken on real field conditions," *Comput. Electron. Agricult.*, vol. 167, Dec. 2019, Art. no. 105093.

[49] M. Kaur and R. Bhatia, "Development of an improved tomato leaf disease detection and classification method," in *Proc. IEEE Conf. Inf. Commun. Technol.*, Dec. 2019, pp. 1–5.

[50] M. Francis and C. Deisy, "Disease detection and classification in agricultural plants using convolutional neural networks—A visual understanding," in *Proc. 6th Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Mar. 2019, pp. 1063–1068.

[51] T. Wiesner-Hanks, H. Wu, E. Stewart, C. DeChant, N. Kaczmar, H. Lipson, M. A. Gore, and R. J. Nelson, "Millimeter-level plant disease detection from aerial photographs via deep learning and crowdsourced data," *Frontiers Plant Sci.*, vol. 10, p. 1550, Dec. 2019.

[52] M. Alruwaili, S. Alanazi, S. Abd, and A. Shehab, "An efficient deep learning model for olive diseases detection," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 8, pp. 1–7, 2019.

[53] S. Mishra, R. Sachan, and D. Rajpal, "Deep convolutional neural network based detection system for real-time corn plant disease recognition," *Proc. Comput. Sci.*, vol. 167, pp. 2003–2010, Jan. 2020.

[54] J. Sun, Y. Yang, X. He, and X. Wu, "Northern maize leaf blight detection under complex field environment based on deep learning," *IEEE Access*, vol. 8, pp. 33679–33688, 2020.

[55] H. Qi, Y. Liang, Q. Ding, and J. Zou, "Automatic identification of peanut-leaf diseases based on stack ensemble," *Appl. Sci.*, vol. 11, no. 4, p. 1950, Feb. 2021.

[56] V. Ravi, V. Acharya, and T. D. Pham, "Attention deep learning-based large-scale learning classifier for cassava leaf disease classification," *Expert Syst.*, vol. 39, no. 2, Feb. 2022, Art. no. e12862.

[57] S. Laosim and T. Samanchuen, "Classification of pomelo leaf diseases using convolution neural network," in *Proc. 18th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON)*, May 2021, pp. 577–580.

[58] C. Chaschatzis, C. Karaiskou, E. G. Mouratidis, E. Karagiannis, and P. G. Sarigiannidis, "Detection and characterization of stressed sweet cherry tissues using machine learning," *Drones*, vol. 6, no. 1, p. 3, Dec. 2021.

[59] C. K. Sunil, C. D. Jaidhar, and N. Patil, "Cardamom plant disease detection approach using EfficientNetV2," *IEEE Access*, vol. 10, pp. 789–804, 2022.

[60] P. Kaur, S. Harnal, R. Tiwari, S. Upadhyay, S. Bhatia, A. Mashat, and A. M. Alabdali, "Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction," *Sensors*, vol. 22, no. 2, p. 575, Jan. 2022.

[61] Q. Wang, F. Qi, M. Sun, J. Qu, and J. Xue, "Identification of tomato disease types and detection of infected areas based on deep convolutional neural networks and object detection techniques," *Comput. Intell. Neurosci.*, vol. 2019, pp. 1–15, Dec. 2019.

[62] G. Irmak and A. Saygili, "Tomato leaf disease detection and classification using convolutional neural networks," in *Proc. Innov. Intell. Syst. Appl. Conf. (ASYU)*, Oct. 2020, pp. 1–5.

[63] G. Dhingra, V. Kumar, and H. D. Joshi, "Study of digital image processing techniques for leaf disease detection and classification," *Multimedia Tools Appl.*, vol. 77, no. 15, pp. 19951–20000, Aug. 2018.

[64] J. G. A. Barbedo, "A review on the main challenges in automatic plant disease identification based on visible range images," *Biosyst. Eng.*, vol. 144, pp. 52–60, Apr. 2016.

[65] Z. Jian and Z. Wei, "Support vector machine for recognition of cucumber leaf diseases," in *Proc. 2nd Int. Conf. Adv. Comput. Control*, vol. 5, Mar. 2010, pp. 264–266.

[66] D. Cui, Q. Zhang, M. Li, G. L. Hartman, and Y. Zhao, "Image processing methods for quantitatively detecting soybean rust from multispectral images," *Biosyst. Eng.*, vol. 107, no. 3, pp. 186–193, Nov. 2010.

[67] V. A. Gulhane and A. A. Gurjar, "Detection of diseases on cotton leaves and its possible diagnosis," *Int. J. Image Process.*, vol. 5, no. 5, pp. 590–598, 2011.

[68] S. D. Bauer, F. Korč, and W. Förstner, "The potential of automatic methods of classification to identify leaf diseases from multispectral images," *Precis. Agricult.*, vol. 12, no. 3, pp. 361–377, Jun. 2011.

[69] P. Revathi and M. Hemalatha, "Advance computing enrichment evaluation of cotton leaf spot disease detection using image edge detection," in *Proc. 3rd Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Jul. 2012, pp. 1–5.

[70] J.-C. Zhang, R.-L. Pu, J.-H. Wang, W.-J. Huang, L. Yuan, and J.-H. Luo, "Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements," *Comput. Electron. Agricult.*, vol. 85, pp. 13–23, Jul. 2012.

[71] S. Naikwadi and N. Amoda, "Advances in image processing for detection of plant diseases," *Int. J. Appl. or Innov. Eng. Manage.*, vol. 2, no. 11, pp. 168–175, 2013.

[72] J. D. Pujari, R. Yakkundimath, and A. S. Byadgi, "Automatic fungal disease detection based on wavelet feature extraction and PCA analysis in commercial crops," *Int. J. Image, Graph. Signal Process.*, vol. 6, no. 1, pp. 24–31, Nov. 2013.

[73] J. D. Pujari, R. Yakkundimath, and A. S. Byadgi, "Recognition and classification of produce affected by identically looking powdery mildew disease," *Acta Technologica Agriculturae*, vol. 17, no. 2, pp. 29–34, Aug. 2014.

[74] J. D. Pujari, R. Yakkundimath, and A. S. Byadgi, "Image processing based detection of fungal diseases in plants," *Proc. Comput. Sci.*, vol. 46, pp. 1802–1808, Jan. 2015.

[75] S. Ghosal, D. Blystone, A. K. Singh, B. Ganapathysubramanian, A. Singh, and S. Sarkar, "An explainable deep machine vision framework for plant stress phenotyping," *Proc. Nat. Acad. Sci. USA*, vol. 115, no. 18, pp. 4613–4618, May 2018.

[76] J. Ma, K. Du, F. Zheng, L. Zhang, Z. Gong, and Z. Sun, "A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network," *Comput. Electron. Agricult.*, vol. 154, pp. 18–24, Nov. 2018.

[77] C. Sullca, C. Molina, C. Rodríguez, and T. Fernández, "Diseases detection in blueberry leaves using computer vision and machine learning techniques," *Int. J. Mach. Learn. Comput.*, vol. 9, no. 5, pp. 656–661, Oct. 2019.

[78] J. Liu and X. Wang, "Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model," *Plant Methods*, vol. 16, no. 1, pp. 1–16, Dec. 2020.

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