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A Systematic Literature Review on Leaf Disease Recognition Using Computer Vision and Deep Learning Approach

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Abstract

Background: Plant diseases affect agricultural output, quality and profitability, making them serious obstacles for agriculture. It is essential to detect diseases early in order to reduce losses while retaining sustainable practices. Plant disease detection has benefited greatly from the use of computer vision and deep learning in recent years because of their outstanding precision and computing capability.
Objective: In this paper, we intend to investigate the role of deep learning in computer vision for plant disease detection while looking into how these techniques address complex disease identification problems. A variety of deep learning architectures were reviewed, and the contribution of frameworks such as Tensorflow, Keras, Caffe and PyTorch to the researchers' model construction was studied as well. Additionally, the usage of open repositories such as PlantVillage and Kaggle along with the customized datasets were discussed.
Methods: We gathered the most recent developments in deep learning techniques for leaf disease detection through a systematic literature review of research papers published over the past decade, using reputable academic databases like Scopus and Web of Science, following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) method for guidance.
Results: This study finds that researchers consistently enhance existing deep learning architectures to improve prediction accuracy in plant disease detection, often by introducing novel architectures and employing transfer learning methods. Frameworks like TensorFlow, Keras, Caffe, and PyTorch are widely favored for their efficiency in development. Additionally, most studies opt for public datasets such as PlantVillage, Kaggle, and ImageNet, which offer an abundance of labelled data for training and testing deep learning models.
Conclusion: While no singular 'best' model emerges, the adaptability of deep learning and computer vision demonstrates the dynamic nature of plant disease recognition area, and this paper provides a comprehensive overview of deep learning's transformative impact on plant disease recognition by bringing together information from different studies.

Keywords: Deep learning, Computer vision, Plant disease, Systematic literature review

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I. INTRODUCTION

Most economies rely heavily on the agriculture sector, which is also the main source of income in many developing countries. According to the World Population Clock, the country's growth rate of population was 0.91% per annum in 2024 [1]. In order to keep pace with the growing human population, a rising trend in agricultural production is necessary to fulfil the food demand, in line with the 2020 Global Food Policy Report. Regardless, fulfilling the current population's need for food is becoming increasingly difficult due to the sneaky plant diseases that are becoming a nightmare for agricultural practitioners [2], [3]. By reducing both the quantity and quality of agricultural products, such diseases are inflicting enormous losses on national economies [2]. Adding to that, agriculture today must deal

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with environmental protection issues, hence there is growing pressure to use fewer pesticides, have a smaller negative impact on the environment and have a lower possible cost of production [4].

Parallel to the Fourth Industrial Revolution (IR 4.0), the agriculture sector has tremendously transformed through smart agriculture. The evolution of technology has led to the transformation of the agricultural sector, which promises an increase in the production rate and improved quality [5]. One of the emerging concepts that refer to managing farms using technologies is deep learning. By mimicking how the human brain works, in which every neuron is connected, deep learning relies on the idea of extracting features from the raw data by employing several layers. By doing so, various qualities that are pertinent to the input data can be recognized [6]. It's crucial to keep in mind that machine learning and deep learning are two separate but closely connected sub-disciplines before delving further into this topic. Simply described, machine learning is a sub-discipline of artificial intelligence, whereas deep learning is a sub-discipline of machine learning.

Deep learning methods have become quite popular in the field of agriculture, particularly when combined with computer vision [7]. The fields of computer vision and deep learning are closely related and have significantly enhanced machines' capacity to perceive and process visual information. Computer vision focuses on enabling machines to extract meaningful information from images or videos, whereas deep learning trains artificial neural networks with massive amounts of data to execute complex tasks [8]. These technologies, when linked together, have an impact on a variety of agricultural tasks, including the identification of plant diseases.

Leaf disease poses significant challenges to agricultural productivity, leading to significant revenue losses and adverse impacts on the environment [9]. Traditional approaches are labor-intensive and have the potential for delayed or erroneous results, emphasizing the need for creative approaches that might overcome these shortcomings. In recent studies, the identification and classification of leaf diseases is being done by researchers utilizing computer vision techniques, particularly deep learning [10]. Many deep-learning models and algorithms that can effectively recognize disease symptoms and extract information from leaf images have been developed by previous researchers [11]. Even with the advancements, some problems still need to be overcome, such as the requirement for larger datasets, enhanced model resilience and improved deep learning model interpretability [12]. Besides, current technologies are frequently not scalable and could not be very adaptable to various crop species and environmental circumstances [11].

Plant disease identification is one of the most fundamental and vital tasks in agriculture. Most of the time, identification is done manually, visually, through molecular and serological testing or by microscopy [13]. The issue with using visual assessments to diagnose diseases is that the person doing the evaluation has taken on a subjective task that makes them vulnerable to cognitive and psychological phenomena that might result in bias, optical illusions and ultimately mistakes [14]. Previous studies have explored this subject for identifying and classifying plant diseases. Some of them investigate motivations, classification techniques, the challenges and future trends of plant disease recognition using deep learning. However, there is still a need for a thorough review that covers a wide range of plant species and focuses on the detection and classification of diseases using computer vision and deep learning techniques. In this systematic literature review, our focus is to provide a valuable contribution, especially on the detection and classification of plant diseases using leaf images, in contrast to prior studies that either provide a general overview or concentrate on a single plant species.

II. Literature Review

A. *Types of Leaf Disease, Symptoms and Causes*

Since plant diseases have a detrimental effect on the growth and yield of premium fruits, they have grown to be a significant problem for farmers. Plant disease, as defined by the Britannica dictionary is a core term in the field of plant pathology, and it describes any illness, ailment or disorder of plants that interferes with their natural structure and growth, lowering their productivity [15]. Plants can suffer from a wide range of diseases, with the most common diseases primarily affecting the fragile leaves [16]. These health conditions, which can be caused by a range of pathogens, including bacteria, viruses, and fungus, can result in substantial economic losses for farmers and gardeners [17].

Fungal infections that penetrate and establish colonies on plant leaves are the main cause of leaf diseases. These infections can manifest as powdery mildew, rust or leaf spot, each of which presents certain challenges for plant management operations and disease control measures [18]. Another important concern is bacterial leaf disease, which is caused by bacterial infections that penetrate and damage leaf tissues. Bacterial blight and bacterial leaf spot are two examples of infections that can cause suffering and financial loss in agricultural settings [19]. Furthermore, viruses that infect plant leaves and interfere with vital physiological functions create major hurdles to the treatment of viral leaf diseases [20]. The tobacco mosaic virus and the tomato spotted wilt virus are two well-known virus species that result in growth retardation, mosaic patterns and leaf curling.

Leaf diseases may exhibit multiple kinds of symptoms, depending on the specific diseases and the type of plant afflicted. Several types of anomalies are common appearances of leaf diseases. For example, a frequent indication of many diseases caused by bacteria, viruses of fungi are yellowing or browning of the leaves [21]. Defoliation or the loss of leaves, is another typical symptom that is often linked to these illnesses [22]. Likewise, plants afflicted with leaf diseases resulting from these pathogens typically exhibit deteriorated plant growth [23].

Many factors that impact the health and vulnerability of plants can lead to leaf diseases. Most of the time, environmental factors such as temperature, humidity and light exposure determine the formation and spread of leaf diseases [24]. Additionally, pathogens have the ability to directly infect and damage leaf tissues, which can cause illness from the outset. Furthermore, plant stress brought on by things like malnutrition or drought can erode plant's defenses, leaving it more susceptible to leaf diseases [23]. Besides, poor crop management approaches, such as improper pruning techniques or insufficient fertilization may provide an environment that is favorable to pathogen growth, raising the risk of disease development [25]. These intricate interactions demonstrate the need of all-encompassing plant health management strategies in horticultural and agricultural contexts to lower the incidences and effects of leaf diseases.

B. Computer Vision and Deep Learning for Leaf Disease Identification

Plant diseases threaten the world's food security by lowering crop yields and resulting in serious monetary losses. Traditional methods of diagnosing plant diseases can be time-consuming, labor-intensive, and may not always produce reliable outcomes. As a result, computer vision has emerged as a useful diagnostic tool for plant diseases in recent years, offering traditional methods a more efficient, accurate and cost-effective alternative [26]. The goal of computer vision is to enable machines to comprehend and interpret visual data from images or videos in a manner comparable to how human perceive the world [27]. In the past, useful data was extracted from images by computer vision algorithms using manual feature creation and rule-based approaches [28]. The identification and management of agricultural diseases are evolving as a result of the use of computer vision in plant disease detection. Computer vision systems are able to completely analyze vast quantities of plant images and identify disease symptoms that have never been observed previously by utilizing sophisticated algorithms [29]. Unlike traditional approaches that rely on manual inspection, these automated systems operate fast and effectively, processing images in a short amount of time and alleviating the stress of farm workers [30].

Computer vision and deep learning are closely related fields that play a significant role in augmenting the capabilities of computer vision systems. In order to incorporate deep learning to create a computer vision-based system for diagnosing plant diseases, a large amount of data must be used to train the model [31]. Typically, the common method in developing this system involves data collection, data preprocessing, model training and finally the evaluation of the model [32]. In order to process the images and improve the quality while reducing noise, a sizeable dataset comprising pictures of both healthy and sick plants must be assembled. To be able to identify patterns in the images while recognizing disease symptoms, the preprocessed images must thereafter be used to train the deep learning model. Next, a test dataset is used to evaluate the trained model's accuracy and performance.

Moving from rule-based techniques to deep learning-based approaches, computer vision has advanced significantly over the past decade [33]. Large datasets like ImageNet and the strength of computing resources, especially the increased availability of computing power and data have fueled this change, enabling machine learning to open up remarkably powerful new possibilities in computer vision [34]. Advancements in computer vision, particularly the shift to deep learning-based techniques, have facilitated new applications and research opportunities, including in plant disease detection. The emergence of the research topic discussed in this systematic literature review is likely a result of these advancements and the need to understand their impact on specific domains or applications.

C. Related Secondary Study

Several more publications comprehensively looked into automated disease detection in agriculture, with a particular emphasis on the use of cutting-edge technology like computer vision, machine learning, deep learning and image processing techniques to identify and classify plant diseases. The evaluation includes a comprehensive review of relevant secondary studies and original research articles. The state of the art in automated disease detection is assessed by combining the results of various studies, highlighting important approaches, challenges and advancements. These studies [35], [36], [37] are retrieved from the Scopus database using the keywords "systematic literature review" and "plant disease detection". A comparative table (as shown in Table 1) is also provided to clarify the distinctions between this SLR and other pertinent studies.

A study by [35] presents SLR that focused specifically on cotton plant disease detection and classification, exploring recent papers that utilize machine learning and deep learning techniques. It provides a detailed analysis of parameters such as dataset set, algorithms used, and performance metrics tailored to the context of cotton plants. On the other hand, [36] conducts SLR investigating the motivations, classification techniques, dataset, challenges and future trends in disease detection across different plant species. In [37], the SLR is dedicated to automatic plant disease detection, delving into the methods and algorithms used specifically for detecting diseases in potato crops. The review emphasizes the application of deep learning algorithms, particularly convolutional neural networks in potato disease detection. Therefore, this study seeks to provide an extensive literature review on various plant species, focusing on the detection and classification of disease on leaf images using computer vision with deep learning approaches.

TABLE 1
RELATED SECONDARY STUDY

Ref	Original Sample (O)	Citation as of April 2024 / Publication	Scope	Approaches
[35]	A Systematic Review on Cotton Plant Disease Detection & Classification Using Machine & Deep Learning Approach	0 / Conference	Cotton Plant Disease Detection and Classification	Machine learning, deep learning
[36]	A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends	5 / Journal	A systematic study on image-based plant disease detection approaches covering both localization and disease classification	Machine learning, Deep learning, Image processing
[37]	Applications of Computer Vision on Automatic Potato Plant Disease Detection: A Systematic Literature Review	7 / Journal	Applications of Computer Vision on Automatic Potato Plant Disease Detection: A Systematic Literature Review	Computer vision

III. METHODS

In the preparation of this review paper, we executed an essential step known as a systematic literature review (SLR) as defined in [38], [39], [40]. This step is considered important because it assists in gaining an understanding of the existing research within our chosen field before further delving into the review process. To improve the transparency of the systematic review, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) techniques serve as a reference [41].

A. Review Planning

For the study to be as thorough and reliable as possible, a systematic review needs to adhere to a few crucial steps. Before conducting the systematic review, a few steps were defined, which will be used throughout the entire review process. This entails formulating research questions to direct the evaluation and create the standards for selecting relevant publications. Subsequently, a search strategy is set up to systematically identify relevant articles from various sources, guaranteeing comprehensive coverage of the subject of interest. Inclusion and exclusion criteria are defined to decide which research can be included in the evaluation. Next, quality assessment approaches are used to evaluate the included studies' methodological rigor and reliability. Data extraction and synthesis processes are used to methodically extract relevant data from the chosen studies and synthesize findings across studies in order to address the research objectives. A comprehensive report is written to disseminate the review's conclusions and findings to interested parties and the greater scientific community after the results have been gathered and analyzed. Fig. 1 shows the main steps to conduct this systematic review.

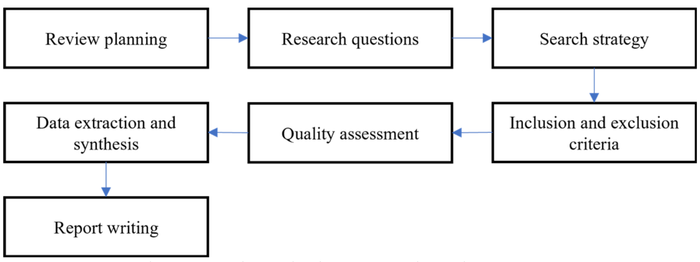

Fig. 1 Key phases in the systematic review process.

B. Research Questions

This review article aims to provide profound insights into the body of research within the domain of deep learning, with a specific emphasis on the detection of plant disease on leaf images implementing computer vision as the main approach with the advancements of deep learning technology. The core objective is to conduct an analysis of numerous

studies from a multidimensional perspective. The following research questions (RQ) serve as a guidance to drive this study.
RQ1: What are the state-of-the-art techniques employed in the detection of plant diseases using computer vision and deep learning?
RQ2: Which tools and frameworks have been predominantly employed in the implementation and development of plant leaf disease recognition systems?
RQ3: Which specific crop have been considered in prior literature concerning plant disease recognition?
RQ4: What dataset is commonly used for researching leaf disease recognition with computer vision and deep learning models?

C. Search Strategy

The search process involved narrowing down the fundamental concepts relevant to this review. Given the extensive range of applications in deep learning, numerous published studies might fall outside the scope of this review article. This SLR concentrates on digital scientific databases, thus excluding any forms of gray literature from the search process. In this study, two top scholarly databases were chosen to conduct the search, World of Science and Scopus [42].

World of Science of WoS, is a well-known database of academic and scientific publications, produced by Clarivate Analytics in 1997. It is a citation index that gives users access to a sizeable library of books, conference proceedings and peer-reviewed journals from a variety of academic fields. On the other hand, Scopus is a multidisciplinary bibliographic database that includes writings from the social sciences, arts and humanities in addition to the sciences, launched by the academic publisher Elsevier in 2004. Since Scopus is a citation index, users may determine which publications have cited that one on how frequently a publication has been cited.

To initiate the process of collecting the study sets, a search string is formulated. Although different indexed research repositories have different formats for creating search strings, a general string was initially created before customizing it for each search engine. The following is the search string primarily used for each database accessed by April 2024.

WoS: ALL=(("leaf disease") AND ("computer vision") AND ("machine learning" OR "deep learning"))

Scopus: TITLE-ABS-KEY (("leaf disease") AND ("computer vision") AND ("machine learning" OR "deep learning"))

D. Inclusion and Exclusion Criteria

To exclude irrelevant studies, the title, abstract and keywords of the research papers were analyzed and graded based on inclusion and exclusion criteria to set the boundaries for this review article. Table 2 illustrates the inclusion and exclusion criteria set out in this study.

TABLE 2
INCLUSION AND EXCLUSION CRITERIA

Inclusion	Exclusion	Description
✓		The focus of the publication is on leaf disease detection using computer vision and deep learning.
✓		The study presents new models or architectures of deep learning in detecting leaf disease.
✓		The publication is written in English.
✓		The publication is published between 2015 to 2024.
	✓	The full text of the publication is not available.
	✓	Publication that is duplicate or already retrieved from another database.
	✓	The publication is a review/survey paper, posters, extended abstract, article summaries, lecture notes and proposal.
	✓	The publication is a grey literature.

E. Quality Assessment

The quality assessment criteria aim to appraise the methodological quality of the research studies, taking into account elements including the study's aim and the methods' suitability in achieving them as defined by [13]. The elements of the research quality evaluation form are listed in Table 3. The criteria were chosen according to how they would affect the overall caliber of the results. The following scale was used to allocate points to each of the criteria for the quality assessment (QA): yes = 1, partially = 0, no = -1. Any criteria scoring below 3 are deemed insufficient and are therefore excluded from this study.

TABLE 3
QUALITY ASSESSMENT CRITERIA

Item	Assessment criteria	Score		
		Yes	Partially	No
QA1	Was the purpose of the study stated clearly?	1	0	-1
QA2	Does the research provide a detailed explanation of the suggested methodology?	1	0	-1
QA3	Has the suggested strategy's effectiveness been proven?	1	0	-1
QA4	Are there citations from other scholarly works referencing the study?	1	0	-1
QA5	Are the limitations of the research clearly delineated and documented?	1	0	-1
QA6	Do the findings of the research contribute to addressing this study's research questions?	1	0	-1
QA7	Does the research significantly expand the use of deep learning or computer vision techniques for leaf disease detection?	1	0	-1

F. Data Extraction and Synthesis

To collect data pertinent to the research topic, we conducted data extraction using a specified extraction form as shown in Table 4. This form allowed us to thoroughly document the primary studies that addressed our research question. In the process of finding the literature, two reliable digital scholarly databases are employed, WoS and Scopus. Fig. 2 illustrates the search and selection process aimed at retrieving high-quality studies. The initial phase involved identifying studies from the selected databases. Out of the 391 studies retrieved, 27 duplicates were identified, resulting in a total of 364 unique studies. Subsequently, after screening for selection criteria and eligibility, a total of 101 studies remained for further synthesis and final selection.

TABLE 4
DATA EXTRACTION FORM

#	Study data	Description	Relevant RQ
1	Title	Title of the paper	Study overview
2	Database	Scopus or Web of Science	Study overview
3	Type of publication	Journal or Conference paper	Study overview
4	Publisher	Journal publisher	Study overview
5	Country	The country where the journal was published	Study overview
6	Year	Year journal was published	Study overview
7	Architecture	What architecture does the study use?	RQ1
8	Model task	What is the task of the model?	RQ1
9	Predominant approach	What is the predominant approach of the selected model?	RQ1
10	Framework/Tools	What framework or tools were used to develop the architecture?	RQ2
11	Type of Crops	What type of crops does the paper study?	RQ3
12	Dataset source	Where was the dataset obtained?	RQ4
13	Dataset accessibility	Is the dataset public or private?	RQ4

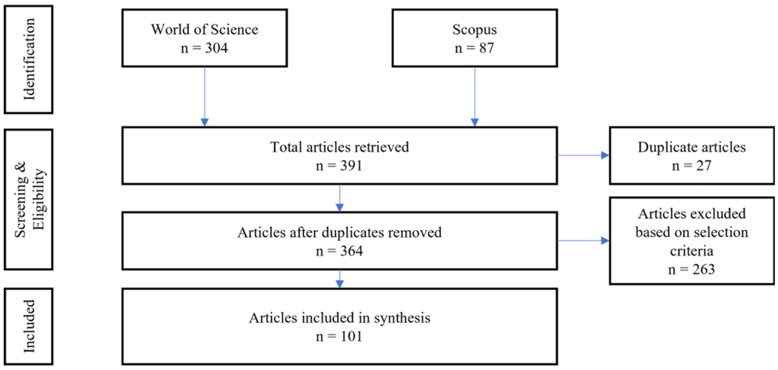

Fig. 2 Study search and selection process – adapted from [43].

By using the search string defined in this study, Fig. 3 depicts the distribution of publications, spanning a decade from 2015 to 2024, across many sources such as journal articles, conference papers and eBooks. Notable differences in publishing frequencies are noted over this period. Eight journal articles and one conference paper were added to the database in the most recent year 2024 for this study. Previous years also showed variations in the number of publications, with 2023 showing the highest number of publications with 19 journal articles and 30 conference papers. In 2022, 12 journal articles and 7 conference papers were selected for this SLR. On the other hand, prior years, like

2019, had much lower publication rates with just one journal article and three conference papers being published. Notably, from 2015 to 2018, no publications were found in any category using the search keywords defined for this study.

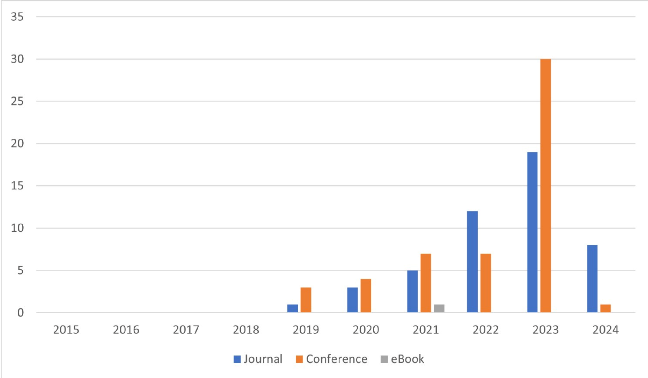

Fig. 3 Distribution of selected publications by year and type of publications.

IV. RESULTS

After reviewing 101 selected studies from two high-quality databases, the results will be presented in the following subsection following the research questions. From the extracted data, a geographical distribution is created, as shown in Fig. 4 to showcase the geographical spread of 108 studies eligible for data extraction and synthesis. The world's most populous nations, including India, China, Egypt, Malaysia, Morocco, Bangladesh, Saudi Arabia, Vietnam, the United States of America, Pakistan and Indonesia were found to be in line with research endeavors and subsequent scientific interest in the identification and recognition of leaf plant disease using computer vision with deep learning approaches.

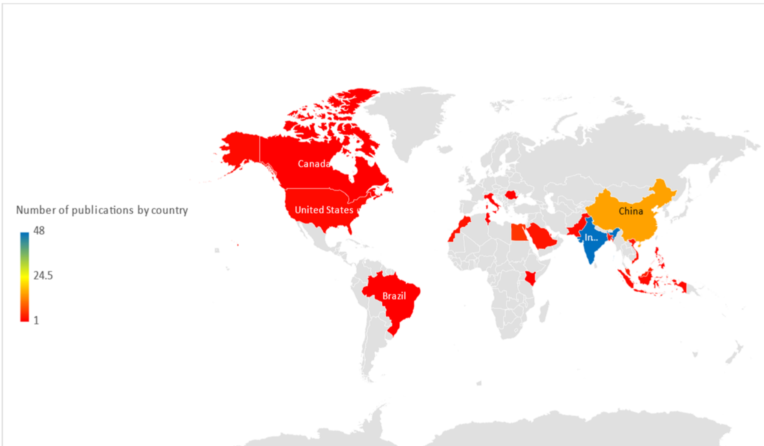

Fig. 4 Geographical distribution of the selected study.

A. RQ1: What are the state-of-the-art techniques employed in the detection of leaf plant diseases using computer vision and deep learning?

Before delving further into the state-of-the-art techniques employed in the detection of leaf diseases, the main focus of the selected study is illustrated in Table 5. The study highlights four primary objectives that become topics of interest among the researchers, which are disease detection, disease classification, severity level classification and early disease prediction. Some researchers have expanded their focus beyond individual tasks, opting to combine two tasks for more comprehensive approaches.

TABLE 5
THE FOCUS OF THE STUDY

Main focus	References	Number of studies
Disease detection	[44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92]	49
Disease classification	[93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117]	25
Severity level classification	[118], [119]	2
Early disease prediction	[120], [121], [122], [123], [124], [125]	6
Disease detection & classification	[126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138]	13
Disease classification & severity level assessment	[139]	1
Early disease prediction & classification	[140]	1
Disease segmentation & detection	[141], [142]	2
Disease segmentation & classification	[143], [144]	2

From the 101 studies, we have grouped the predominant approaches of the researchers into 19 groups, which are comparative study, custom classifier, custom layers, custom layers and feature extraction, custom layers and image segmentation, ensemble model, hybrid architecture, hyperparameter tuning, hyperparameter tuning and optimizer selection, image embedding, image segmentation, model enhancement, new architecture, optimizer tuning, transfer learning, transfer learning and feature extraction, transfer learning and hyperparameter tuning, transfer learning and image segmentation, and transfer learning and custom classifier. Table 6 summarizes the predominant approach for each study.

TABLE 6
THE SUMMARY OF THE PREDOMINANT APPROACH

Predominant approach	References	Number of studies	Percentage of usages (%)
Comparative study	[44], [45], [93], [94], [95]	5	5.0
Custom classifier	[96]	1	1.0
Custom layers	[46], [47], [48], [49], [50], [97], [98], [99], [121]	9	8.9
Custom layers & feature extraction	[100]	1	1.0
Custom layers & image segmentation	[51], [126]	2	2.0
Ensemble model	[101], [102], [127]	3	3.0
Hybrid architecture	[52], [128]	2	2.0
Hyperparameter tuning	[53], [54], [55], [103], [104], [105], [106], [118], [119], [122], [129], [130], [140]	13	12.9
Hyperparameter tuning & optimizer selection	[56], [57], [58]	3	3.0
Image embedding	[59]	1	1.0
Image segmentation	[60], [61], [107], [131], [141], [142], [143]	7	6.9
Model enhancement	[62], [63], [64], [108], [109], [144]	6	5.9
New architecture	[65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [110], [111], [112], [123], [124], [132], [133], [134]	19	18.8
Optimizer tuning	[76], [77], [113]	3	3.0
Transfer learning	[78], [79], [80], [81], [82], [83], [84], [85], [114], [115], [120], [135], [136]	13	12.9
Transfer learning & feature extraction	[86], [87]	2	2.0
Transfer learning & hyperparameter tuning	[88], [89], [90], [91], [116], [117], [125], [137], [138]	9	8.9
Transfer learning & image segmentation	[92]	1	1.0
Transfer learning & custom classifier	[139]	1	1.0

B. RQ2: Which frameworks/tools have been predominantly employed in the implementation and development of plant leaf disease recognition systems?

The tools and frameworks predominantly employed in the implementation and development of leaf disease recognition systems include MATLAB, Tensorflow, Keras, PyTorch, OpenCV, Pillow, Streamlit, Flask, Darknet and Caffe. The summarized version showing the tools and framework utilized is presented in Table 7.

TABLE 7
LIST OF FRAMEWORK/TOOLS EMPLOYED IN PREVIOUS STUDY

Framework / Tool / Library	References	Number of usages
MATLAB	[60], [87], [120], [137]	4
TensorFlow	[45], [48], [49], [50], [57], [58], [64], [75], [84], [85], [92], [95], [98], [99], [100], [102], [106], [109], [113], [117], [126], [134], [136], [138], [140], [142], [143]	27
Keras	[44], [48], [49], [50], [53], [64], [65], [66], [75], [76], [79], [84], [85], [88], [92], [93], [98], [99], [100], [103], [104], [106], [110], [111], [113], [117], [122], [125], [132], [134], [138], [140], [141], [142], [143]	35
PyTorch	[52], [55], [56], [61], [73], [74], [90], [91], [118], [131]	10
OpenCV	[50], [64], [85], [100], [118], [134]	6
Pillow	[118], [134]	2
Streamlit	[116]	1
Flask	[78]	1
Darknet	[121]	1
Caffe	[46], [50]	2

C. RQ3: Which specific crop has been considered in prior literature concerning plant disease recognition?

From the extracted studies, it appears that tomato is the preferred crop among researchers [49], [58], [67], [68], [69], [73], [81], [84], [85], [89], [90], [100], [105], [113], [116], [127], [128], [131], [133], [134], [136], [140], with 22 studies focusing on this particular plant species. Following closely behind is rice, with 11 studies [54], [64], [79], [80], [93], [102], [111], [114], [117], [138], [144] selecting it as their primary crop of interest. Fig. 5 provides a summarized overview of the crops that have been primarily chosen by researchers.

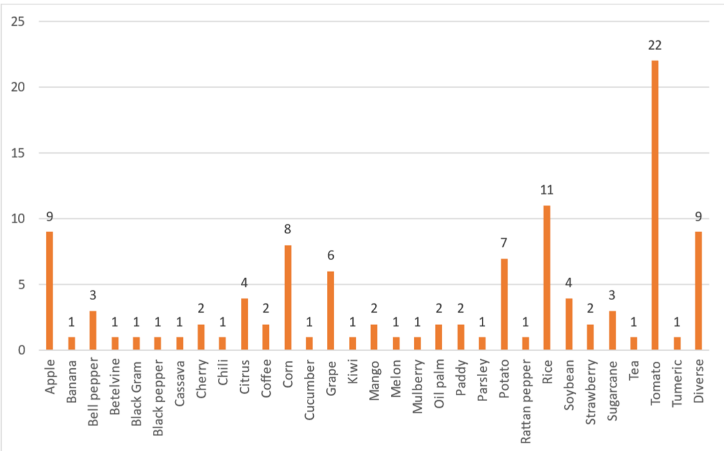

Fig. 5 Number of crops that were mentioned in 101 selected studies.

D. RQ4: What dataset is commonly used for researching leaf disease recognition with computer vision and deep learning models?

In the summary process, it was revealed that researchers acquire datasets for their studies through three primary methods, which are public datasets (68%), self-collected datasets (24%), and a combination of both, termed hybrid datasets (8%). Public datasets are openly available repositories of annotated images, while self-collected datasets are gathered by researchers through their own data collection efforts. Hybrid datasets combine images from both public repositories and the researcher's own collection efforts. For the public datasets, researchers have selected from various repositories, including ImageNet, Kaggle, PlantVillage, Mendeley, AI Challenger, PlantDoc, UCI (The University of California) database and Plant Pathology database. PlantVillage emerges as one of the most frequently chosen databases, with 28 out of 69 studies utilizing it. Kaggle follows in 17 out of 69 studies, and PlantDoc is used in 4 out of 69 studies.

The distribution of public datasets is summarized in Fig. 6. In terms of data environment, most researchers opt to utilize data collected in real-world environments (94 studies) rather than controlled settings (2 studies). Additionally, some researchers combine real-world data (3 studies) with controlled environments for a more comprehensive dataset.

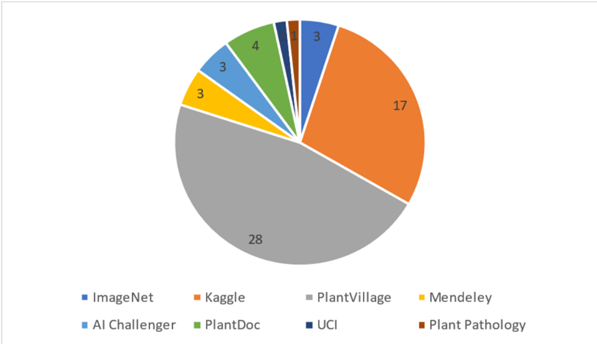

Fig. 6 The distribution of public datasets across 69 studies.

V. Discussion

A. RQ1: What are the state-of-the-art techniques employed in the detection of plant diseases using computer vision and deep learning?

In the selected studies, the focus of leaf disease identification was divided into seven classes. The first one is disease detection, where this approach involves only detecting plant diseases without classifying them. 51 studies are focusing on this specific task. Next is disease classification, where this study involves classifying the diseases based on their symptoms. 27 studies have adopted this approach of classifying leaf diseases. Among the researchers, some have combined these two tasks doing both disease detection and classification, which are 13 studies altogether. Some researchers focus on early disease prediction, where they focus on predicting the onset of a plant disease before the symptoms appear as has been done by 6 studies. Also, some researchers opt for classifying the leaf disease based on their severity level as has been done by two studies. Other researchers such as [140] focus on combining two tasks, which are early disease prediction and classifying them according to their disease. Some of them first classify the disease and determine its severity level as has been done by [139].

Subsequently, in this study, we have divided 19 categories of the predominant approaches among the researchers; comparative study, custom classifier, custom layers, custom layers and feature extraction, custom layers and image segmentation, ensemble model, hybrid architecture, hyperparameter tuning, hyperparameter tuning and optimizer selection, image embedding, image segmentation, model enhancement, new architecture, optimizer tuning, transfer learning, transfer learning and feature extraction, transfer learning and hyperparameter tuning, transfer learning and image segmentation, and transfer learning and custom classifier. The first one is the comparative study which involves comparing different deep learning architectures for plant disease detection and classification, in which 5 studies have been doing this [44], [45], [93], [94], [95]. The second one is a custom classifier, where this approach involves customizing the classifier for the detection and classification of leaf disease [96]. The third one is custom layers, where this approach involves customizing the layers for deep learning architectures [46], [47], [48], [49], [50], [97], [98], [99], [121]. One study [100] customized the layers of the architecture before extracting the features of leaf disease. Two of the studies [51], [126] involve designing custom layers for deep learning architecture used in plant disease detection and classification, along with image segmentation techniques.

[101], [102], [127] do the ensemble model, where this approach refers to combining multiple deep learning models to improve the accuracy of the detection. Besides, some studies tune the hyperparameter [53], [54], [55], [103], [104], [105], [106], [118], [119], [122], [129], [130], [140] and some of them also select the best optimizer along with the hyperparameter tuning[56], [57], [58]. Out of 101 studies, one study [59] goes for embedding the leaf images into a lower-dimensional space while preserving their essential features for plant disease detection and classification. There are seven studies [60], [61], [107], [131], [141], [142], [143] that focus on dividing images into meaningful segments to detect and classify plant diseases. It helps in identifying disease areas within the plant images. Six studies including [62], [63], [64], [108], [109], [144] do the model enhancement. In this approach, existing deep learning models are refined and optimized to improve their performance in the identification of leaf diseases. In these studies, this may involve fine-tuning the model parameters or architecture or even selecting the best optimizer for the model.

Several researchers designed novel deep-learning architectures specifically tailored for plant disease detection and classification. These architectures offer improvements over existing models in terms of accuracy or efficiency. Most of the researchers designing novel deep learning commonly use CNN as their base algorithms. A study [113] developed an optimized capsule neural network (CapsNet) based on CNN and a study [100] developed a custom parallel deep CNN-based. Study [65] builds a new architecture by integrating PSPNet and CNN, which is called P-CNN. Researchers [112] make use of CNN to develop black gram leaf disease detection, which is named BPLF-10 based on CNN. A study from [52] developed a hybrid transformer based on CNN architecture, called FOTCA. In this study, F and O represent Adaptive Fourier Neural Operator (AFNO) and TCA refer to Transformer-CNN architecture. In [123], the researchers developed a new architecture, named Avert-CNN to evaluate critical diseases in grapevine leaves, while [73] made use of CNN architecture to create a novel lightweight CNN to detect tomato disease, termed as LightMixer. ConvPlant-Net was introduced by [68] for the detection of tomato, pepper bell and potato disease, and [69] created a novel PCA DeepNet based on CNN in order to detect tomato leaf diseases. Additionally, a shallow CNN was created by [72] in the detection of diverse crops, and [66] made use of deep CNN to design a novel SoyNet in classifying soybean leaf diseases.

Besides designing new architecture, many researchers also opt for transfer learning as this approach can help in reducing training time and cost. Since pre-trained models have already been trained on large datasets for general tasks, they have learned useful features from diverse data. The amount of effort and processing power needed to train a new model from scratch can be greatly decreased by using these pre-trained models. Many researchers employed transfer learning [78], [79], [80], [81], [82], [83], [84], [85], [114], [115], [120], [135], [136] either with custom classifier [139], image segmentation [92], hyperparameter tuning [88], [89], [90], [91], [116], [117], [125], [137], [138], and feature extraction [86], [87].

As a whole, from the extracted studies, we can observe that transfer learning becomes one of the most predominantly chosen by the researchers with 26 studies out of 101. Transfer learning improves model generalization, particularly in situations where the target task has limited labelled data. Improved performance can be achieved by fine-tuning pre-trained models to adapt to the specific target domain. More importantly, designing new architectures allows researchers to modify the model's structure to fit the particulars of plant diseases, perhaps leading to improved performance over generic architecture. Furthermore, new architectures provide chances for creativity and methodological investigation, driving advancements in the field of plant disease recognition. Absolutely, the choice between transfer learning and developing new architectures depends on various factors, such as the requirements of the task, the availability of labelled data, computational resources, and the researchers' expertise.

B. RQ2: Which tools/frameworks/libraries have been predominantly employed in the implementation and development of plant leaf disease recognition systems?

From the extracted studies, we can observe that Tensorflow is the most commonly used in the creation of plant disease recognition systems, with 27 times being mentioned. This is perhaps because deep learning and machine learning have widely adopted it and found it to be popular. With 35 mentions, Keras is another popular framework for plant disease identification because of its versatility, simplicity of usage and ability to operate on top of TensorFlow or Theano. Pytorch is another popular choice with ten mentions in previous studies. It is a useful tool for diagnosing plant leaf problems because of its dynamic circulation graph and automatic differentiation abilities. With one mention in the selected studies, Flask is a Python web framework for developing online applications. Because of its ease of use and simplicity, one of its prominent uses is the detection of plant leaf diseases. Darknet is a neural network framework for object detection and recognition, where it has been mentioned once in the reviewed literature. It is a helpful tool for object recognition in images. Caffe is a deep learning framework for image recognition and classification that has received two mentions. Its ability to recognize and classify images makes it a helpful tool for diagnosing plant leaf diseases.

Furthermore, OpenCV is a computer vision library that is commonly utilized in the development of plant leaf disease detection systems, with six references. Because of its extensive collection of image processing and feature extraction methods and tools, it is a valuable resource for diagnosing plant leaf diseases. In addition, Pillow framework, which has received two mentions, is a Python imaging module for image processing and feature extraction. One of the most often used applications in plant leaf disease detection because of its simplicity and low complexity. Finally, a Streamlit is a Python web application development library that has only been mentioned once. Its ease of use and capacity for creating interactive web applications make it a valuable tool for diagnosing illnesses of plant leaves.

C. RQ3: Which specific crop has been considered in prior literature concerning plant disease recognition?

When it comes to the identification of plant diseases, important questions emerge about whether particular crops have been the focus of previous research. To comprehensively address this question, we conducted a thorough survey of existing research, analyzing the percentage of various crops that have been the subject of investigation. Our analysis revealed notable trends in research focus, with tomato emerging as the most prominently studied crop. Following closely behind are rice, apple, corn, potato, grape, citrus, and soybean. Due to their widespread cultivation and consumption, these crops are both important for food security and have a substantial economic impact. Effective disease management techniques are therefore more important to guarantee their availability and production going forward. Moreover, from the previous studies, we can see that many diseases can seriously affect the yields and quality of tomato, rice, apple, maize, potato, grape, citrus and soybean crops. They are more likely to be investigated in relation to the identification of plant diseases because of their high disease prevalence.

On the other hand, crops like banana, betel vine, black gram, black pepper, cassava, chilli, cucumber, kiwi, melon, mulberry, oil palm, parsley, rattan pepper, tea and turmeric, each only explored once in the previous research. After being observed in the previous study, these crops might be less need for study on the management of diseases if they are less prone to disease. Also, these crops might not be grown or consumed as extensively, for instance, which would lessen the demand for efficient disease control techniques.

D. RQ4: What dataset is commonly used for researching leaf disease recognition with computer vision and deep learning models?

We may deduce from the chosen studies that the three primary categories of datasets that researchers use are public, self-collected and hybrid datasets. 69 studies have used public datasets, which are the most often used. These datasets have been deliberately chosen by multiple researchers and are publicly available. They provide a thorough depiction of the facts and are frequently broad and varied. The ImageNet, Kaggle, PlantVillage, Mendeley, AI Challenger, PlantDoc and the UCI database are among the public datasets that the search results pointed to. With eight research using hybrid datasets, they are the second most popular type of dataset. To build a more comprehensive dataset, these datasets combine data from multiple sources, including self-collected and public datasets.

Lastly, just 24 studies have employed self-collected datasets, which is a lower usage rate. These datasets may be smaller and less varied than public datasets because they are usually gathered by lone researchers or groups. In these studies, most researchers collected their own datasets from selected farms and orchards, allowing them to control the data environment settings. In general, self-collected datasets may need a substantial amount of funds and resources for collection and curation, whereas public datasets are preferred since they are more affordable and easily accessible. Moreover, the collection and curation of self-collected datasets may require a substantial time and effort commitment.

VI. CONCLUSIONS

To investigate the state-of-the-art techniques for identifying plant diseases from images of the leaves using deep learning and computer vision, we conducted a comprehensive and methodical assessment of the literature for the purpose of this study. As per our findings, the techniques that are most frequently utilized include image segmentation, custom layers, transfer learning and development of new architecture. Transfer learning enables pre-trained models to be readily adaptable to the target domain, which helps handle problems with limited labelled data or similar underlying issues. On the other hand, the development of novel architectures offers researchers greater flexibility and customization, allowing them to appropriately tailor models to the characteristics of plant disease identification. Additionally, we have also discovered the most popular framework for this particular study, such as Tensorflow, Keras and Pytorch, as well as the most popular crops, which include tomato, rice and maize. While no definitive consensus emerges on the ‘best’ model, our findings consistently demonstrated that the accuracy and efficiency of plant disease detection and classification may be greatly increased by utilizing computer vision and deep learning approaches.

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